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EFFECTS OF ANALYST TARGET PRICE REVISIONS ON SHORT-TERM STOCK RETURNS

Master's Thesis
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Abstract of master's thesis

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Abstract

This master's thesis focuses on researching whether analyst target price revisions affect short-term stock returns in the Helsinki stock exchange and if so, would investors be able to benefit from this phenomenon by utilizing a target price -driven investment strategy. The returns of the strategy are benchmarked against the OMXH25GI index returns. From a theoretical standpoint, target price revisions should not affect stock prices according to the efficient market hypothesis, and it is also reviewed from this perspective whether the Helsinki stock exchange meets this condition.

The results were achieved by utilizing statistical methods and returns calculations, while the validation was conducted through stock price forecasting. According to the results, target price revisions do affect stock prices in the short term, to an extent that an investment strategy based on them could be viable. By following the investment strategy presented here yielded aggregate returns of 31.1 % and 15.9 % by following stocks or estimators respectively, while the benchmark reached 9.8 % during the same time period. As the individual returns are relatively low due to the short holding period, the strategy is characterized by high volumes and rapid reactions to revisions.

The returns of the investment strategy vary greatly on the stock- and target price issuer level, which is easily observable and thus exploitable, making it relatively easy to beat the benchmark, at least according to the results discovered here. Revisions also clearly affect other stock metrics as well, such as volume and number of trades, implying that market participants actively attempt to benefit from the reactions caused by them.

According to the findings of the thesis, the theoretical efficiency of the Helsinki stock exchange is questionable, despite the data consisting of its most liquid stocks. From the perspective of a private investor, the most relevant finding was that target prices are inaccurate and often incorrect, but abnormal returns should be achievable by exploiting the reactions caused by revisions.

Keywords target price, efficient market hypothesis, analysts

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Tiivistelmä

Tämän maisteritutkinnon tutkielman aiheena on selvittää, mikäli analyytikoiden tavoitehintojen julkistuksilla on vaikutusta osakkeiden lyhytaikaiseen kurssikehitykseen Helsingin pörssissä, ja mikäli sijoittajat voisivat hyötyä tästä mahdollisesta ilmiöstä käyttämällä tavoitehintoihin perustuvaa sijoitusstrategiaa. Kyseisen strategian tuottoja verrataan OMXH25GI-indeksin tuottoihin. Teoreettisesta näkökulmasta tavoitehintojen päivitysten ei tulisi vaikuttaa osakkeiden tuottoihin tehokkaiden markkinoiden hypoteesin perusteella, ja Helsingin pörssin tehokkuutta arvioidaankin tutkielmassa tästä näkökulmasta.

Aihetta tutkittiin käyttämällä tilastotieteellisiä menetelmiä sekä tuottolaskelmia ja tulosten validointiin käytettiin osakkeiden hintaennusteita. Tulosten perusteella tavoitehintojen päivitykset vaikuttavat osakkeiden hintoihin lyhyellä aikavälillä, jopa siinä määrin että niihin perustuva sijoitusstrategia vaikuttaisi olevan kannattava. Tässä tutkielmassa esiteltävän sijoitusstrategian mukainen tuotto oli 31,1 % ja 15,9 % osake- ja liikkeellelaskijan tasolla, verrokki-indeksin yltäessä 9,8 % tuottoon samalla aikaperiodilla. Sijoitushorisontin lyhyydestä johtuen yksittäisten sijoitusten tuotot jäävät mataliksi ja strategiaa kuvaavatkin korkeat volyymit ja nopea reagointi uusittuihin tavoitehintoihin.

Sijoitusstrategian tuotot vaihtelevat merkittävästi osakkeiden ja tavoitehinnan liikkeellelaskijoiden tasolla, joka on helposti havaittavissa ja hyväksikäytettävissä, joten vertailuindeksin tuoton ylittämisen tulisi olla kohtuullisen helppoa tulosten perusteella. Tavoitehintojen uusimien vaikuttaa selkeästi myös muihin osakkeiden mittareihin, kuten volyymiin sekä kauppojen lukumäärään, joka implikoi markkinaosapuolten pyrkivän aktiivisesti hyötymään niiden aiheuttamasta reaktiosta.

Tutkielman tulosten perusteella Helsingin pörssin tehokkuus joutuu kyseenalaiseen valoon, vaikka dataan sisällytettiin vain sen likvideimmät osakkeet. Yksittäisen sijoittajan näkökulmasta tärkein havainto oli, että tavoitehinnat ovat epätarkkoja ja harvoin oikeassa, mutta niiden julkistusten aiheuttamia reaktioita hyödyntämällä ylituotot ovat saavutettavissa.

Avainsanat tavoitehinta, tehokkaiden markkinoiden hypoteesi, analyytikot

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1 Introduction

An example of a short-term stock price sprint driven by a target price release is Inderes' revision for Incap on 25.5.2020 – one of many which were the main motivators for choosing this topic. The stock price change from the aforementioned day to the next day's opening price was 8.9 %, with the revision day's lowest price being €11.61 and the revision value being €14.00. As there were no announcements from the company's side or major news about the company, the target price revision was the primary cause for the price hike. The stock price continued on a high level well into July and saw more increases after earnings announcements and outlook updates. Such a rapid price change driven by revisions is not that common, but it highlights how investors might not act rationally on the market. Incap is, however, a momentum stock and investors might have taken this positive insight from an estimator as a signal that the positive momentum is going to continue. Incap's market capitalization is not that high, and price changes of this scale are more common with smaller firms than larger ones (Han & Kim, 2019. Incap was not part of the data used for the analysis in this thesis, but this case was just provided as an example of a drastic price change driven by a target price revision.

Financial analysts ("analysts") give and update target prices for stocks based on valuations, forecasts, company announcements and analyses. These updates, or revisions, typically reflect the most recent information released by companies; typically quarterly reports, 10-K's (annual reports) or profit warnings. Press releases might also justify revisions, depending on their importance. Target prices, and reports that they are based on, provide investors with insight about stocks' future outlooks, risks and performance. Earlier research (Bradshaw & Brown 2006) has shown that analysts are able to provide value through these reports by being able to forecast future stock performance, to an extent. However, rational choice theory is the cornerstone of economic research which assumes that each individual makes decisions based on justified assumptions and hence acts rationally (Scott, 2000). Practice and earlier research (Feldman, Livnat & Zhang, 2012) has shown that target prices have an observable effect on short-term stock returns which contradicts with this assumption. In this context, the term "estimator" is used to describe equity research firms, whose analysts issue target prices to stocks.

The notable impacts that target price adjustments have on short-term stock returns may be due to a plethora of reasons. The most natural cause would be that investors, especially private ones, react to positive or negative target price revisions accordingly in order to reflect on the changes in companies' business outlooks or performance. Another possibility is that institutional investors react to target prices in order to benefit from the known volatility that they cause based on technical analysis and past outcomes. The third is similar to the second one, when private traders attempt to take advantage of stock price changes fueled by target prices. Earlier research (Han & Kim, 2019) and analysis conducted in this thesis shows that it is the traders and institutional investors that most likely use revisions in search of returns, as the correlation between target price implied returns and short- or long-term stock returns is rather weak. Feldman, Livnat & Zhang (2012) found out that earnings revisions -based portfolios yield higher returns in the longer term, although target price revisions do drive returns beyond the short-term to an extent as well.

Given the volumes required to significantly impact stock price intra-day, it seems logical that institutional investors are very much involved in reacting to target price updates. But as in many other cases of trading and technical analysis, strategies are based on anomalies and realized outcomes; thus there most likely has been a trend at some point in time that caused the market to noticeably react to target prices. This is in the core of this thesis – given the assumption that individuals act rationally and make justified decisions on the market, target prices should not affect stock prices as much as they do in practice. Target prices are based on analyses and valuations that are updated once relevant information is released by companies and hence there is a delay in the target price update compared to when the information is released. Each market participant has access to the same information as the analysts and they are able to adjust their valuation of the company before the target price is updated, which is typically observable from the initial reaction to the announcement and through the post-earnings announcement drift. However, target price updates often cause a reaction as well, which is peculiar from a theoretical standpoint.

The objective of this thesis is to study whether target price revisions have a significant and observable effect on short-term stock returns and to formulate an investment strategy based on reacting to target price revisions in order to see if it could yield higher returns than the comparison index. The reactions to target prices will also be reflected from the viewpoint of the efficient market theory – should there be a strong reaction to target price releases when the information that the forecasts are based on has already been available before target price revisions are published?

Research questions:

Do analyst target price revisions affect stock returns in the short term?

Could investors be able to benefit from an investment strategy based on these effects if they exist?

Would this investment strategy be viable in practice and what are the potential returns?

There exist earlier studies about the same subject, and perhaps the most similar is by Feldman, Livnat and Zhang (2012). Other studies address some aspects of this thesis but not completely, and in most the timeframe is much longer than the rather short one used here. All studies find that target prices themselves aren't that useful, but they do contain valuable information especially if the analysis behind the target price revision is provided, and that revisions have implications on stock returns. The main point of this thesis is to test whether an investor would be able to exploit the potential abnormal returns caused by target price revisions rather than use its information contents.

2 Literature review

2.1 Overview

2.1.1 Target prices

Traditionally, target prices have been parts of sell-side analysts' equity reports which started to be widely undisclosed in the 2000s (Brav & Lehamy, 2003). Nowadays, some estimators revise target prices even without equity reports to reflect the most recent information released to the market. In a sense, target prices are analysts' educated guesses about future stock prices. The time horizon is typically 12 months, but six-month target prices are not uncommon either. Target prices are different from earnings forecasts in multiple aspects, mainly in regards to accuracy, regulation and audience (Bilinski, Lyssimachou & Walker, 2013). They are typically based on an analyst report generated after an earnings announcement, which is when the analyst revises their estimations about future earnings and cashflows of the company; which can be used to come up with an estimate about the stock price development - the target price. Thus, they do not necessarily reflect how much the stock should cost currently, but rather in one year into the future or during the 12-month period. A target price can be considered as a stock's return potential on the market, indicating what kind of price level should be possible in 12 months. This is where earnings forecasts and target prices differ most, as the former focuses more on the company's potential to generate earnings while the latter is also heavily influenced by the stock market and sentiment (Bilinski, Lyssimachou & Walker, 2013).

Bradshaw & Brown (2006) describe that analysts take multiple factors into account that affect the stock price potential, from earnings reports to stock momentum and characteristics, such as liquidity, and often conduct both technical and fundamental analysis. The target price is different to intrinsic value due to the limited time horizon, although the inputs could be very similar. From a momentum point of view, stock prices can be inflated (deflated) due to a variety of reasons, ranging from trends to poor performance of other investment options, or even because of passive management. Hence, target prices reflect the price potential during a 12-month period and due to the nature of target price revisions, recommendations may conflict with the current stock price. Analysts rarely update target prices if an earnings announcement is due soon, even if a major press release was just released (Inderes, 2018).

Target prices can also be generated without an equity report, which typically increases the frequency of revisions as the most up-to-date information can be hastily reflected on the target price. This was observed in the analysis section, where some estimators released substantially more revisions than others, who often issued less than 10 revisions per stock in a year. Bradshaw & Brown (2006) find that not only does a high revision frequency have little to do with target price accuracy, but they also note that past good track record in revision accuracy does not correlate with the future success rate, and imply that luck plays a bigger role in accuracy consistency than skill.

2.1.2 Analysts

Target prices are formulated by analysts who aim to set stocks an analysis-based price that reflects current and future outlooks for the business, usually 12 months ahead. Analysts include both buy- and sell-side ones, with the former using analyses to come up with investment opportunities and the latter issues buy, hold and sell recommendations for stocks. In this thesis the focus will be on sell-side analysts, as they provide the target prices in addition to recommendations which are important for private investors, perhaps even more so than the prices themselves (Inderes 2020). Often the analysts focus on a specific industry and several companies operating within it since there are multiple industry-specific phenomena and metrics that require certain domain to understand and account for. Earlier research (Bilinski, Lyssimachou & Walker, 2013) has proven that analysts typically tend to be able to predict future stock performance and that there is indeed value in the reports, valuations, and recommendations that sell-side analysts issue. However, Bradshaw & Brown (2006) find conflicting results in their article, which is covered in more detail in the accuracy section. Whether the stock returns are a cause of analyst recommendations is a topic of its own, but it must be acknowledged that this is a possibility (Doukas et al. 2005).

There often is variation between target prices that are adjusted according to the most recent information, which is particularly interesting from the viewpoint of this thesis. If there are differing opinions on valuation inputs that result in different recommendations; how can a private investor decide which analyst is correct – or why does their own analysis results in a different price? Analysts’ differential ability to provide relevant forecasts in terms of revisions is of dispute, and for instance Bradshaw & Brown find no such ability while Bilinski, Lyssimachou & Walker do. The former only used US data while the latter examined other markets as well, which might affect the results.

The media often uses mean target prices as the "real" value of a stock, and this, the consensus, is then compared to the current stock price to see whether it is under- or overvalued (Demirakos, Strong & Walker, 2010). Simply put, this kind of comparison reviews by how much the market as a whole is wrong about the "real" price that's often an average of analysts' target prices. This mindset that is being fed through most financial media leads private investors to doubt their own views and place high value on target prices that are hopefully objectively formulated, which may have multiple implications. Target prices are rarely met and according to Bradshaw & Brown (2006), only 45 % of stocks reach their target prices at any point during the 12-month timeframe. The consensus is also used to review the boldness of revisions, that is, by how much do individual revisions differ from the mean forecast value.

2.1.3 Recommendations

Sell-side analysts issue buy, hold and sell recommendations for stocks which are typically based on the difference between the current stock price and target price. Recommendations have been found out to have as an, or even more, important role in affecting stock prices than target prices (Jegadeesh et al., 2004). Analysts use the same public information released by companies that investors can access in addition to industry insights and personal remarks when valuing a company and its target price potential. Target prices, and reports they are based on, offer private investors valuable information in a more readable and summarized form than company releases. Recommendations are the simplest way to base investments on, as they are direct calls to action for investors. From the perspective that each market participant is rational and wants to maximize their own value, the importance of analyst reports should not be as high as it is, since generating a thorough report based on earnings announcements takes time, and individuals have time to update their own valuations before analyst reports are published. Recommendations can be problematic if investors act upon them consistently, as the individuals most likely don't base decisions on their own analysis. Hence, not all market participants can be seen as rational if they react blindly according to analyst reports (Bilinski, Lyssimachou & Walker, 2013).

Stock recommendations may contradict with target prices even though they are often based on the forecasts used to come up with target prices. Since target prices often have a relatively short timeframe, they may conflict with longer-seeing recommendations. Thus, recommendations rather try to capture whether a stock is a good investment in the long term based in firm characteristics, industry and competitive advantage whereas target prices attempt to estimate the stock's return potential in typically 12 months. Jegadeesh et al. (2004) argue that recommendations favor stocks with better quantitative traits, while those with less favorable characteristics perform poorly. According to them, changes in the consensus do however have observable effects on future returns.

2.2 Revision characteristics

In this subchapter, some common traits and critique of revisions are covered. As target prices are often limited to a 12-month time period, this causes issues for both the analysts and investors alike. Due to the observed effect of revisions on stock returns, some studies have argued that estimators might use target prices for market manipulation and to cater them to their own interests (Lai, 2004).

2.2.1 Short-term focus

Target price updates and analyst forecasts have been criticized for their short-term focus and low accuracy (Demirakos, Strong & Walker, 2010), as the target price is often different to the intrinsic value of the firm. Target prices are based on short-term earnings forecasts and are thus revised after each earnings announcement or other major announcement. From the perspective of long-term and value investing the short-term focus is harmful as it may cause excessive volatility for the stock price. Target prices do not necessarily reflect the analysts' estimate of the intrinsic value of a security as it is only one-year forward-looking and multiple market-based variables need to be accounted for when coming up with the target price. Subjectivity and optimism play a much bigger role in determining a target price than a present value of a bond, for instance (Bradshaw & Brown, 2006; Chiang et al., 2016).

2.2.2 Optimism

Optimism is argued to plague target prices. According to Brav & Lehavy (2003), the average one-year-ahead target price is 28 % higher than the then current stock price – few stocks yield such returns in only a year. Bradshaw & Brown (2006) found out that only 45 % of target prices were met during the 12-month horizon, and only 24 % of stocks were at or above the target price at the end of the period. Thus, analysts typically issue ambitious target prices that are met in less than half of the instances. Lack of compensation, responsibility and focus on earnings have been presented as the major reasons for analyst over-optimism. In this sense, investors should be better off by deriving relevant information out of target prices and should use it in their own investment decision making rather than naively trusting target prices. As Han & Kim (2019) concluded, after the initial shock upon a revision, the stock price tends to drift in the opposite direction. Hence, investors should be able to benefit from target prices with the least effort by focusing on utilizing them in the short-term. Even though target prices do carry relevant information to investors, using that information may be difficult for novices and the threshold to focus on short-term "trading" is lower, albeit it may not be profitable if the transactions are of low value due to transaction costs.

A somewhat worrisome discovery is that the estimators' clients are the companies the analysts are issuing the forecasts to, and that the rewards tend to be biased towards optimistic forecasts. In a time series from 1983 to 2011, analysts miss on the same side 32 % of the time; with an annual revision count $n >= 20$ the fraction of everyone missing is 19 %, while in $5 <= n <= 9$ the share is 39 %, with the size of observations being 53 % and 27 %, respectively. Thus, the percentage of all analysts missing on the same side grows drastically when n is lower. During the aforementioned time horizon, optimism in general has been declining and pessimism has increased in terms of all analysts either missing above or below actual earnings. More advanced forecasting methods have possibly reduced over-optimism and made target prices more realistic, but the rising share of too pessimistic forecasts also sheds light onto the difficulties of forecasting stock returns (Chiang et al. 2016). Yet, as only 45 % of target prices are met at any point in 12 months, they are still inaccurate even if less optimistic. Optimism can also be explained by analysts' high hopes that target prices will gravitate into fundamentals in the future, i.e. placing too much weight on best-case scenarios.

2.2.3 Forecast bias

A conclusion can be drawn from Bradshaw & Brown's (2006) article that analyst optimism is at least partly caused by biases. In aggregate, analysts' personal biases tend to lead to a systematically biased market. In order to capture this, analysts tweak their target prices to reflect different market biases, such as momentum and firm characteristics. Personal biases, on the other hand, include customer relationships and shading of forecasts. Typically, the companies that the analyst is issuing target prices to is the customer of the estimator and in order to maintain a good relationship, target prices may be adjusted to being more optimistic. As an example of how forecasts can be manipulated, analysts may restrict from reacting to an unbiased signal if the rewards of doing so are sufficient enough (Chiang et al. 2016). In practice, if a customer is satisfied with an analyst not reacting to relevant information, the reward may overweigh the truth.

Systematic bias as a result of aggregated individual biases may also affect target prices, but it is hard to judge whether an analyst is biased and to what extent (Chiang et al. 2016). As a result, optimism and biases have significant effects on target prices which may be why stock prices often move to the opposite direction in the mid-term after the initial price shock upon target price release (Han & Kim 2019).

2.2.4 Target price informativeness

Target prices carry important information about factors that are often otherwise unobservable to investors, namely discount rates and risks. Since the most common target price formulation method is based on earnings multiples, investors are able to estimate the weight of other factors when only future earnings are observable (Da, Hong and Lee 2016). For instance, investors may use the target price and forecasted earnings to come up with the analyst's projected P/E ratio and compare that to the historic ratios. Since earnings multiples are most commonly the base of target prices, investors can see whether the revised target price is based on earnings growth, or P/E ratio which carries information about future risks and growth.

Discount rate shifts can be interpreted through target prices as well. Lower target prices can be seen as an indicator of a higher future risks due to changes in the discount rate (Han & Kim 2019). In practice, this is relevant as Da, Hong and Lee (2016) find that 30 – 51 % of target price revisions are caused by discount rate shifts. Although earnings are still the most important factor across all scenarios, reverse-engineering the discount rate factor from target prices may be very informative to investors.

Due to analyst optimism and general target price inaccuracies, the prices themselves are often only indicative. 12 months is a long period of time for forecasting a stock price, and even the most well-argued and -valued target price may be completely wrong due to unforeseen events. Thus, investors benefit most from picking relevant information out of revisions reports or by reacting to recommendation changes or target price implied returns. As target prices are extremely difficult to get right, they are less regulated and valued than earnings forecasts for instance. The objective of this thesis is to see whether investors could benefit from price shocks caused by revisions in the short term, which places little weight on the correctness of the target prices themselves. In the analysis section, it becomes apparent that there are differences in how the market reacts to revisions by different estimators, while there are differences among stocks too.

Ho, Strong & Walker (2018) find that if anything, revisions have strong effects on negative returns. This might be due to general analyst optimism, and once negative revisions are published, they come as a surprise to the market. The authors do mention that in general, companies tend to withhold negative information more than positive, and thus it’s intuitive that the market reacts more strongly to negative information in a consistent stream of positive outlooks and estimations.

2.2.5 Revision manipulation and institutional ownership

Chen et al. (2016) find in their article that less experienced investors tend to follow analyst recommendations and target prices more than their more experienced peers, which might cause analysts to transfer risks on target prices by exploiting the tendencies of less experienced investors. This strategy might be exploited by institutional investors that have observed the reactions to revisions and adjust their own positions accordingly, by taking advantage of decisions made by less-informed investors. Adjusting target prices based on the anticipated market reaction is referred to as the catering theory, where analysts offer the market something that is expected from them, instead of providing objective insights (Lai, 2004). This theory helps shed light on the consistent optimism of analysts; the market expects optimistic revisions and that is often catered to them. This sort of protocol reduces the informativeness of target prices and their accuracy, both of which have been under scrutiny in multiple academic studies (e.g. Bradshaw & Brown, 2006; Chiang et al., 2016). As found in earlier literature and also in this thesis, it seems that the sentiment of a revision is more important than the value itself; meaning that the values are often only seen as indicative, and it's considered more important whether a stock has up- or downside potential. Thus, by providing a biased revision an analyst can potentially affect stock returns quite significantly, even though there would be very little to justify that. This can be exploited relatively easily as revisions noticeably influence stock returns.

Bilinski et al. (2015) argue that high short-term institutional ownership is correlated with analyst's biased target prices but not with earnings forecasts. This is indicative of the previous notions that target prices are often more inaccurate than earnings forecasts, due to lack of compensation and regulation. Thus, analysts seem to be more concerned about the accuracy of earnings forecasts, which impact their own track record and compensation, while target prices can even be used to influence stock price development – which is evident by the correlation between short-term institutional ownership and biased revisions.

2.2.6 Target price formulation methods

Firm valuation can be conducted in a number of ways, by using techniques like the discounted cash flow model (DCF), sum-of-the-parts, the comparables model or even dividend discount model. Depending on the type of the company and industry, some models fit the purpose better than others. DCF is perhaps the best universal model as it does not require dividends to be calculated, and cash flows are the most robust and accurate figures companies provide, and analyst cash flow and earnings forecasts are often relatively accurate. The comparables model and dividend discount can be used for quick valuation to see whether a stock if under- or overvalued given the current parameters but there is no forecasting involved, other than the assumed growth rate of dividends. Sum-of-the-parts on the other hand is useful for conglomerates and companies with distinct units to identify potential in different business units. Sometimes well-performing units may be held back by poorer ones and restructurings may enable companies to unlock higher value, which can be very much justified if some units decrease aggregate firm value (Da, Hong & Lee, 2016).

Valuation is subjective, as the likelihoods of events and weights on different factors differ between analysts. Thus, valuation is often a process of finding an indicative intrinsic value of a firm, or the fair value of a non-public company. Target prices and their analyses may contain similar inputs and methods as valuations, but as the stock price is formulated on the market, other aspects need to be considered in addition to firm-specific ones. Also, as the horizon for a target price is typically only 12 months, valuations and target prices may be very different. There is significant variation between target prices as well, and the consensus is used to describe analyst expectations in general (Chiang et al., 2016). In this thesis it will be examined whether there are differences in market reactions to different target price issuing entities, i.e. do market participants react differently to target price updates, and if forecast accuracy plays a role in this. The assumption is that not all market participants act rationally, and that estimator track record, image and branding may affect investor behavior.

In practice, analysts tend to use more simplified methods for target prices than valuations, in particular earnings multiples are favored over DCF valuations (99 % and 13 %, respectively). Earnings multiples take into account different industry-dependent factors and stock pricing -derived factors more than DCF, which is better for determining the intrinsic value of a security. It has been argued that the most important role of analysts is forecasting earnings, thus it is natural that target prices are mostly based on earnings multiples (Da, Hong and Lee 2016).

Contrary to the efficient market theory, according to which new information should immediately be reflected in respective stock prices, stocks tend to slowly drift towards the direction that the new information suggests. This same phenomenon is observable with target prices, although it is partly explained by the post-earnings-announcement drift (PEAD). During an earnings surprise, stocks are rarely priced correctly immediately after the earnings announcement and the price slowly drifts towards it (Bernard & Thomas 1989). What is noteworthy is that while an earnings surprise unsurprisingly causes strong stock price changes, target price revisions also seem to cause similar reactions even though they are based on the information released by the company earlier. Stock prices even tend to drift to the opposite direction of a revision-based price shock, which might be explained by a market overreaction (Han & Kim 2019).

About one third of earnings forecasts and target price revisions occur within three days of an earnings announcement. Target price revisions yield abnormal returns upon release, with an annualized return of 11.3 % on average and an additional 2.6 % if the revision occurs within three days of the earnings announcement in a hedge portfolio. These findings further contradict with the efficient market theory and shows that overall, the market underreacts to newly released information, as both earnings announcement and target price revisions yield abnormal returns immediately upon release (Feldman, Livnat & Lee 2012). From the viewpoint of this thesis this is particularly interesting and goes to show that markets are not as efficient as one might think, although the returns were noticeably lower in the data used here.

2.2.7 Criticism against consensus

In their article, Han & Kim (2019) made an interesting discovery that investing against target prices and the consensus in particular can be beneficial in the long term. They found out that a strategy that is based on the most pessimistic and optimistic analyst recommendations yields significant abnormal returns. This can be simplified to buying recent winners and losers; where the first has momentum and the latter sees consistently underwhelming stock returns. Stocks sometimes perform poorly due to analyst optimism and even pessimism, which is often uncalled for (Bradshaw & Brown 2006). Overly optimistic forecasts lead to inflated stock prices, and continued analyst pessimism may hinder the effects of positive earnings surprises. Han and Kim also showed that the consensus forecast is often wrong, as it is prone to systematic bias as noted by Chiang et al. (2016). They described that stock performance is often inversely correlated with the consensus, which sounds quite contradictory. The returns in their study were realized in a much longer timeframe than what is used in this thesis, though, but these findings shed light onto market inefficiencies and on the poor quality of analyst target prices. In short, Han & Kim bet on outlier target prices, which turned out to be a viable strategy – making the role of "average" target prices questionable.

2.2.8 Limits to arbitrage

Limits to arbitrage has been used to explain multiple anomalies observed on markets (Green et al. 2017). A commonly used method is to exclude micro stocks from samples, as they might offer arbitrage opportunities due to limited liquidity. Arbitrage can also be limited due to restrictions placed on funds, causing inefficiencies to exist for extended periods of time. The data used in this thesis only comprises of the biggest companies listed on the Helsinki stock exchange in part to address this anomaly, but also due to the fact that small stocks rarely have more than one or two analysts following it, which places too much weight on subjectivity.

In earlier studies, it has been found out that there are factors that limit arbitrage and its potential for reaching abnormal returns using a target price -based investment strategy.

Particularly, transaction fees often shrink achieved returns to the extent that the strategy is barely viable (Han & Kim 2019). However, practice has shown that this short-term trading is common across multiple markets, and institutional and active traders may be able to make up for the transaction costs through high volumes – otherwise there would not be such strong reactions to target price revisions. Free trading services like Robinhood bridge the gap between amateur and professional traders in terms of transaction costs, making more and more trading strategies viable to investors with relatively small volumes.

From the viewpoint of this thesis the limits to arbitrage are particularly interesting, as theory, and earlier research has suggested that they should be able to prevent achieving abnormal returns using a target price -driven trading strategy. In the Helsinki stock exchange reactions to target price revisions are so strong that transaction fees alone seem unable to outweigh the returns of the strategy.

2.2.9 Accuracy

Forecast accuracy is not necessarily as simple as checking whether the actual outcome is the same as the forecasted one. What is considered accurate enough is also relevant. In the case of target prices, informativeness is even more important than accuracy, according to the findings of this thesis.

Target price accuracy is typically judged by checking whether the objective was met or not during the 12-month forecast period. But in terms of informativity and relevance, it is not necessarily that simple. For instance, stock X currently costs €8, and analysts A and B have simultaneously issued target prices for it, €9 and €12, respectively. After one year, stock X costs €11. According to a black and white definition of accuracy, analyst A would have been correct and B incorrect. But which target price was more relevant to an investor; which one was closer to the current price and was able to foresee the price hike? This example was meant to give fuel for thought about the informativeness of target prices – a conservative one is a safe bet, but not necessarily that informative while an ambitious, properly argued target price gives investors more insight. Naturally, not all stocks can be issued with ambitious target prices if the fundamentals are not there, but it seems that analysts favor optimistic forecasts for the current stock price instead of a clean slate approach for the target price formulation according to the analysis conducted for this thesis. That is, that analysts issue highish expectations for the current stock price (Han & Kim, 2019), that leads to optimism, but often fail to see major changes in fundaments that enable high stock returns in the future, like in the case of NESTE where target prices were consistently pessimistic across the data used.

As target prices are often, at least partially, based on valuations, which in turn use earnings forecasts, it is rather interesting as to why target prices are so seldomly met. Obviously, market dynamics affect stock prices a lot, and it is not always easy to foresee different market reactions. Thus, multiples are more commonly used in target price formulation than DCF, for instance. Da, Hong and Lee (2016) note that only 13 % of analysts use DCF in formulating target prices and P/E multiplied by earnings is the most common method. The earnings multiples approach might not be the most justifiable one, but in practice market dynamics make it extremely difficult to base target price revisions solely on company-specific factors. Still, analysts are optimistic in general about target prices which in turn lowers their accuracy.

Analysts show a much greater accuracy when they forecast earnings while target price accuracy and consistency is low. Bradshaw & Brown (2006) speculate that most analysts are incentivized based on earnings forecasts, while there is no similar practice with target prices. Feldman, Livnat and Zhang (2012) find that from a dataset of over 1.1 million earnings forecasts, there are target prices for only 40 % of the observations and hence they are much less common. Analysts do not randomly issue target prices for the sake of it, but the lack of incentives and market dynamics affect forecast accuracy which might decrease the overall popularity of issuing target prices.

2.2.10 Returns reversal

Han and Kim (2019) found out in their study that after the initial shock upon target price releases where stock prices tend to follow the direction of the target price implied returns, the following performance is often the opposite – which is called returns reversal. This is odd given the initial reaction, but also contradictory to the post-earnings-announcement drift; where the market reacts to new information slowly rather than quickly as suggested by the efficient market hypothesis. From the viewpoint of this thesis this is interesting, since if stocks drift in the opposite direction than what the target price suggests, this means that the stock will react strongly to a newly issued target price even though there would be no major changes in the value itself. This was observed for some, but not all, stocks in the analysis section but as the focus here is on short-term returns rather than mid-term, the potential returns reversal was only partially addressed in the analysis.

In the chapters to follow the research questions will be answered through analysis of the largest stocks of the Helsinki stock exchange. First, the data will be described and the preprocessing steps are covered, before moving on to exploratory data analysis and final results. The main findings of the analysis were that target prices do exhibit relevance to investors based on the consistent effects they have on short-term stock returns, but there are differences between estimators in terms of their ability to accurately formulate target prices and in their ability to affect stock returns.

3 Research strategy

The objective of the thesis is to test whether target price revisions affect stock returns in the short term and whether a viable investment strategy can be formulated based on revisions. The research method is a quantitative, empirical-analytical approach that utilizes past stock and revision data, while findings are drawn by comparing returns around revisions to stock- and index level returns. The focus here is to analyze the effects of revisions on the estimator- and stock level, without examining individual analysts. Although it has been shown that differences exist on the analyst level too (Bradshaw & Brown, 2006), the author believes that there was not sufficient data to expand the analysis further. Also, as the findings were significant enough on the estimator- and stock level, there was no need to dig deeper in order to find relevant insights.

The implications of revisions on short-term stock price changes will be tested with means of statistical analysis, returns calculations and stock price forecasting. Initially, the focus is on researching the general characteristics of target prices, e.g. accuracy, and finding a possible correlation between recently issued revisions and stock returns. Based on the findings, further analysis is carried out accordingly in hopes of finding patterns and anomalies that could potentially be exploited by investors.

Target price accuracies and intra-day returns are looked into first at the stock level, as it is assumed that high target price accuracies might correlate with stock returns, as accurate forecasts could be informative to investors (Han & Kim, 2019). Next, three-day window returns are calculated around revision days, as this metric is also used in earlier literature (Bradshaw & Brown, 2006) and those returns are compared to the average returns of the respective stocks. Stock turnover is also analyzed around revisions and lastly, it is investigated whether the revision signal, i.e. up- or downside, is relevant for next-day returns, which in turn would perhaps be relevant to investors. The different analyses are carried out on both the stock- and estimator level in hopes of discovering relevant insights, as earlier studies have found out that differences exist on both levels.

After examining the implications of revisions, an investment strategy is formulated with the objective of testing whether reaching abnormal returns is possible by utilizing target price implied returns (TPIRs) as the basis of the strategy. Each revision is compared against the current stock price to determine TPIR, and the investment decision is made according to the implied return – to go long or short. The investment is realized the next day at the closing price of the stock, and the transactions are summed together to get the aggregate return at the stock or estimator level. The returns are then compared to find insights and to check the viability of the strategy by benchmarking it against individual stock returns and the OMXH25GI index.

Lastly, an AI algorithm is used to forecast stock prices 47 days in advance. Two datasets are used in the forecasting – one with target price data and the other without. This is conducted to find out whether the inclusion of target price data improves the forecast accuracy. The forecast is solely used to objectively test the relevance of target price revisions; if the forecast accuracy is better when revision data is included, revisions should be relevant for stock price development.

3.1 Methodology

The trading strategy is of a long-short type, where stocks with a positive implied target price return are purchased and those with a negative one are shorted. The returns for each stock using this strategy are aggregated for the calendar year and the whole time period and compared to the respective stock's returns and the OMXH25GI dividend-free index.

It is assumed that the investor is able to purchase the stock at the previous day's closing price, and that the stock price is fixed even though the target price would be issued at a later time during the day. This simplifies the calculations and should not significantly influence the results as a whole. It is possible, and in multiple instances it was the case, that multiple revisions take place on the same day. This makes it difficult to determine which, if any, revision caused the possible price change, but this was not addressed per se. In the forecasting phase, the day's mean revision value was used to avoid having more than one row of data for each day. The estimators were also analyzed in hopes of finding differences between them in terms of market reactions, as the next-day stock returns often behaved counterintuitively, i.e. not according to daily consensus, following multiple revisions being issued on the preceding day. This led to the assumption that the market reaction might depend partly on the estimator.

Basic calculations in the analysis include the daily and three-day returns on or around revision days, and mean stock returns across the dataset. In order to mitigate the impact on the opening price should the revision occur outside the Helsinki stock exchange opening hours (10-18:30 EET), the previous day's closing price was used instead. After-hours trading may affect the opening price if a revision is published outside the opening hours, thus this procedure was used. Transaction costs are assumed to be fixed at 0.4 % per transaction, which is a bit high for an active trader, but it also includes costs related to overnight shorting. The transaction costs will be included in the return calculations, as they add up to a sizable amount due to the high volume of trades.

The differences between estimators will be examined by calculating their target price accuracies and number of revisions issued in addition to comparing their performance based on the TPIR strategy. It was relevant to find out for how many stocks they issued revisions to in order to help understand their performance. For instance, the average number of revisions issued per stock by an estimator was six and if the quantity deviated from that noticeably, it would perhaps affect the estimator's performance and also raise questions as to why that was. Target price accuracies will be examined by comparing the target prices to the respective stock prices after 12 months. Naturally, the higher the deviation between the anticipated and realized stock price, the lower the accuracy. Further analysis was carried out on certain aspects should interesting findings emerge.

3.2 The TPIR strategy

The revision-based strategy (TPIR strategy) that the investments are based on revolves simply around the idea of following the target price implied returns as a buy or sell signal. If TPIR is positive, it is considered a buy signal and vice versa. Thus, an investment is made upon each revision and in this case, the long or short position is realized the next day following the revision. This means that the number of transactions is high, which combined with the rather small individual returns might be risky and it takes quite a lot of effort compared to passive investing. On the other hand, an investor only has to examine the newly released target price and compare it to the current stock price in order to decide whether to go short of long, which is relatively simple compared to some other trading methods. The assumption is that revisions spark market reactions and that there is at least some positive correlation between TPIR and future returns, which seems to be sound based on the data, for the most part. But as mentioned before, the signal seems to be more relevant than the scale of the implied return.

The short position is taken by agreeing to pay the "prior" price of the stock, or the closing price of the day prior to the revision. Thus, if the stock price goes down, the return is achieved by being able to purchase the stock from the market at a lower price than what was agreed. Conversely, if the stock price should go up, the stock has to be purchased at a higher price than in the short position, leading to losses. The long position is taken by purchasing the stock at the prior closing price and the stock is sold the day following the revision at the closing price. The short position is theoretically riskier, as the potential loss is infinite as stock prices can always go up. The maximum loss in a long position is the invested capital, and the transaction costs of acquiring the stock. No leverage is used in the analysis but using it might be justified as the individual returns are relatively small in scale.

Short positions require a margin account, i.e. a credit account for lending shares, and there are differences between costs and pricing related to it. Some brokers do not charge more than the transaction costs for intra-day shorting, but overnight positions often see additional costs, such as credit and account-related costs. Thus, as a compromise to take overnight shorting costs into account, the transaction cost used in the analysis here is 0.04 % - a basis point higher than the common transaction cost in Finland for an active trader. Transaction costs vary greatly depending on the trader's activity and instruments used, the use of derivatives typically comes at a higher cost than just buying and selling stock and thus, the transaction costs depicted here are only for illustrative purposes.

3.3 Forecast algorithm

The effects of revisions on future stock prices were also tested by forecasting the stock price with two datasets – one with and one without revision data. The algorithm used in the model is long short-term memory (LSTM), which is a deep learning neural network. It was selected due to its suitability for the problem, whereas the commonly used gradient boosting algorithm XGBoost had some limitations, which could be addressed but given the author's limited knowledge in machine learning algorithms the LSTM was chosen instead, frankly because it was easier to apply. The biggest limitation to XGBoost was that without some relatively cumbersome adjustments, the algorithm could not exceed the maximum value in the train data which proved problematic especially in ELISA's case, which saw its stock price increase in the test data over the train data prices. The objective for the model was set to minimize MSE, which was considered purposeful in this case.

The point of the model was not to reach for high accuracy scores or tune it to achieve the best performance, but rather to compare the differences between the model's capability to forecast future stock prices with or without target prices. The results were insightful for the stocks selected, ELISA, FORTUM & STERV; with the first ones seeing a lower mean squared error (MSE) when target prices were not included in the model and vice versa for the last. Minimizing MSE was considered a purposeful objective for this case and the results were insightful. Some compromises had to be done in order for the forecast to work as intended, which will be covered in more detail in the results section.

4 Data

The data comprises of stock price and transaction data in addition to revision data from companies listed on the Nasdaq OMX Helsinki stock exchange, with the OMXH25 index being the basis of the stock data. This was due to a variety of reasons, mainly because there seems to be no previous analysis of the effects of target prices from the Helsinki stock exchange, unlike from bigger exchanges. Since the size of the exchange is relatively small, only the 25 most-traded stocks were chosen which had an aggregate market capitalization of some €260 billion at the end of 2019 (Pörssisäätiö, 2020). Chiang et al. (2016) noted in their article that the same-side forecast errors increase substantially as the number of analysts following a stock decreases, thus the 25 most-traded stocks were selected for the analysis to ensure sufficient liquidity and number of analysts. A high share of same-side misses implies optimism or bias, and thus this was mitigated by using high-volume stocks only.

One of the objectives of this thesis is to examine whether the efficient market theorem applies to the Helsinki stock exchange and if market reactions to revisions can be exploited by investors, and perhaps the best way to do this is to check whether it applies to its most liquid stocks. If information is not reflected timely on liquid stocks, it's not most likely the case for smaller stocks either. Further, if there are not enough analysts covering a stock, then target prices may become too subjective. Obviously, the aggregate analysts bias as suggested by Chiang et al. (2019) can be present, but it is common in many markets and hence reflects the actual trading environment.

As shorting is also utilized in the analysis, the stocks available for shorting are primarily the ones included in the OMXH25 index. There are exceptions, but for instance many OMXH small cap stocks cannot be shorted. Further, as even the 25 most-traded stocks in the Helsinki stock exchange are rather small in an international context, including more anomaly-prone small cap stocks is not justified and they are often left out in similar comparisons as well.

The data was obtained from the I/B/E/S database and the Nasdaq OMX Nordic website, with the first used for target prices and the second for stock price and transaction data. The time period of the data is 19 months, from January 1st, 2018 to July 31st, 2019. The reasons for the relatively short time period are two-fold. The target price data was gathered in the beginning of 2020, and I/B/E/S only shows data that's more than six months old, thus the latest target price data was from July 2019. Later on during the year, I/B/E/S was no longer accessible by the author as the faculty's access to the system had expired, and the already-acquired data had to be used. Still, 2630 individual target price forecasts were available in the final data alongside with 8620 price data points. The time period of the data was normal in the sense that there were no major crises or out-of-the-ordinary changes to the OMXH25 index and thus the results should be valid and applicable to similar economic environments.

It is noteworthy that the data from I/B/E/S does not show names for all estimators, as estimators have been given the option to hide their name. Estimators which have opted to do so are named "PRMDN" followed by a four-digit number to mask their names. There is no clear reason why estimators would choose to do so, but one can speculate that perhaps it has something to do with hindering benchmarking efforts – a good track record is not necessarily worth hiding. Also, as a notion, the stocks were not divided into portfolios prior to the analysis unlike in some studies. This was mainly due to the relatively low number of stocks and differences between them.

The data was in csv and Excel format from I/B/E/S and the Nasdaq Nordic website, respectively. Both records were imported into a Jupyter notebook, where the preprocessing and analysis was conducted using the Python programming language, mostly by utilizing the pandas software library, which is commonly used for data manipulation and analysis. Basic calculations were performed using the standard Python functions and some libraries, but the stock price forecasts utilized the long short-term memory (LSTM) neural network architecture. Graphs, tables and figures were produced either by using Python's plotting packages or standard tools and Excel, depending on whichever was more purposeful or relevant.

4.1 Return calculations

As some revisions were published on holidays or weekends, these dates were shifted to the next business day. This ensured that all revisions had their corresponding stock price data available and reflected real life in the sense that an investor is only able to purchase a stock when the market is open.

In the first parts of the analysis, the impact of target prices on stock returns was calculated during and around the target price announcement day, in the latter by using the opening price of the day before the target price revision and the closing price of the day after it. The previous and next days were naturally business days and thus had stock price data available. If the target price was released on Friday, for instance, the next Monday's stock price was used by utilizing the Python pandas business day function. This was used to come up with the return around the target price release, the same method was used in studies by Bradshaw & Brown (2006) and Chiang et al. (2019). Despite the magnitude of target price revisions, there seemed not to be a strong reaction in the intra-day price on the target price announcement day, hence the three-day window approach was implemented. This might be due to the same phenomenon as in the case of the post-earnings-announcement drift; in practice new information is not immediately reflected on security prices in full but rather the information signal causes prices to start drifting towards the "correct" price. Thus, using three-day returns in addition to intra-day is relevant.

The three-day approach was selected due to presence in earlier research and also, due to the fact that using e.g. five days, which was also used in some studies, the results were more mixed and the longer the time period, the more events may unfold that aren't related to revisions. As a sidenote, the three-day approach was only used to capture the effects of revisions compared to "normal" days to see whether there are major implications. When calculating the target price -driven investment strategy returns, the previous day's closing price was used instead of the opening price as the investor cannot know in advance when revisions are published. The previous day's closing price was used since a revision may be issued outside the stock exchange opening hours, which may affect the revision day's opening price through after-hours trading. The difference between the previous closing and next opening price is often small, but since short-term returns are not that great either it was relevant to take the potential effects of after-hours trading into account.

4.2 Metrics

Target price implied return (TPIR) describes the theoretical returns based on the revised target price; the relation between the current stock price and target price. This metric is used heavily in this thesis to describe the up- or downside potential of stocks in the eyes of analysts. An implied return greater than one means that the target price is above the then current stock price and vice versa. The consensus target price is often used by the financial media to capture the market's expectations for stocks. Here, the consensus is referred to and addressed in some sections, but the main focus is on finding differences between estimators and stocks; the consensus has little effect on short-term returns upon revisions. The TPIR is also used to see whether the magnitude, or scale, of it has effect on the returns. Instinctively, the higher the TPIR the higher the return should also be, but that is not necessarily the case as found out in the results section.

The return based on revisions was calculated by either using the three-day window approach or next-day returns. The former was used to examine whether abnormal returns exist around revisions, and the latter was used to calculate the potential or attainable returns of utilizing revisions as an investment strategy. The target price accuracies were calculated by comparing target prices to actual, respective stock prices in 12 months' time. The smaller the deviation between the two, the better the accuracy. The accuracies were only calculated for revisions issued between January and July of 2018, as there was no corresponding stock price data available beyond July 2019. This time period proved sufficient to find insights and differences between estimators, and as target prices in general are relatively inaccurate due to the difficulty of stock price forecasting, there wasn't a need to expand the accuracy analysis.

4.3 Data preprocessing

The original data from the two datasets was very purposeful and thus there was very little that had to be done to it to enable analysis. Stocks of merged and acquired companies were dropped, dates were converted to a pandas-supported format and SEK-value target prices were dropped. Also, Kesko's stock price was multiplied by three as the stock saw a split in the spring of 2020 with a ratio of 3:1, and the target prices were estimated based on the pre-split stock value while the stock price data was already converted to reflect the split. Further, some columns from the target price dataset were dropped due to low or no value in terms of the analysis, most importantly the target price activation dates which indicate when the respective target price was activated in the I/B/E/S database. For the analysis, the announcement date was used instead, as it indicates the date and time at which the information was released to the market by the estimator. The forecast horizon was also dropped, as the focus in this analysis is target price revisions' implications on short-term returns and thus the forecast horizon has little relevance from this perspective.

As mentioned, the stocks used in this thesis consist of those listed in the OMX Helsinki 25 index, the 25 most traded stock in the Helsinki stock exchange, but some were dropped due to lack of data and other reasons. For instance, The I/B/E/S database didn't contain consistent data for Nordea (NDAFI), mostly due to mixing of SEK target prices with the EUR value stock traded in OMX Helsinki, and fetching the correct exchange rate for each revision instance would've been cumbersome. This was the case with Telia (TELIA1) as well, as the target prices were clearly of SEK value despite some marked as EUR. I/B/E/S did not contain data for YIT (YIT) either, hence it is not part of the data. Amer Sports (AMEAS) was dropped during preprocessing due to lack of price data from the Nasdaq website as the company was acquired in the spring of 2019 and was then delisted. After the preprocessing was done, there were 21 stocks left. As the OMXH25 index saw relatively many changes during the 19-month time period, having as much as 21 stocks is positive.

Once the two datasets were preprocessed, they were merged into one, so that there was corresponding price data for each respective revision based on date and stock. At this stage, the correlation between daily returns and target price implied returns was 0.43. For further analysis, two data points from the surrounding business days around the target price revision date were added, i.e. price data from the previous and next business day. This was done to enable the analysis of stock price development around the target price release. The Python pandas calendar was used to identify business days and since the US and Finnish business days differ somewhat, there wasn't data for all actual OMXH trading days across the dataset; but this has minimal effect on the results as a whole.

4.4 EDA

The market capitalization of a stock often reflects the number of analysts following it, although it is not the only factor affecting analyst coverage. Each stock in the data used here has at least two analysts covering it, while the highest number of analysts per stock is 28, as seen from Table 1 below. Notably, KOJAMO and TYRES had very few estimators and revisions. TYRES' revision data become available on I/B/E/S late, only in June 2019, thus generalizations cannot be drawn based on a two-month horizon, but the results later on still show how it compared against other stocks. KOJAMO simply had a low quantity of both estimators and revisions, but being a new company in the OMXH25 index, including it in the analysis made it interesting to see how it fared among more established stocks.

Table 1: Number of estimators and revisions per ticker

Ticker	Estimators	Revisions	Rev. / Est.
CGCBV	10	75	7.5
ELISA	22	163	7.4
FORTUM	27	177	6.6
HUH1V	7	55	7.9
KCR	13	61	4.7
KEMIRA	11	35	3.1
KESKOB	9	49	5.4
KNEBV	28	205	7.3
KOJAMO	5	15	3.0
METSB	10	81	8.1
NESTE	21	232	11.0
NOKIA	28	223	8.0
ORNBV	9	46	5.1
OUT1V	20	236	11.8
SAMPO	23	176	7.7
STERV	16	119	7.4
TIETO	10	26	2.6
TYRES	2	7	3.5
UPM	16	175	10.9
VALMT	12	69	5.8
WRT1V	19	206	10.8

Table 1 shows the aggregate statistics about the number of estimators and revisions issued for each stock. The mean number of estimators was 15 and the mean revision quantity was 116. The average number of revisions issued by estimators was 6.9, although there's clear variation between the stocks. The highly volatile OUT1V saw both most revisions issued and the frequency was the highest as well, followed by Neste, which saw strong price growth during the period. It seems that the more stable the company and industry, the less revisions are issued, which is intuitive. A high revision frequency combined with a strong market reaction would be ideal for investors looking to benefit from the increased volumes upon revisions, but the highest returns are achieved by stocks with very average statistics as discovered later in the results section.

After conducting EDA and calculating returns around revisions, the analysis was taken to the estimator- and stock level. Stock returns, changes in volumes and target price accuracies were calculated, before analyzing the potential returns of using the target price -driven investment strategy. Lastly, the effects of target prices on stock price development were tested by conducting stock price forecasts by using the LSTM algorithm, where the performance of the dataset containing revision data was compared to the benchmark. The findings will be covered next.

5 Results

In this section, different kinds of analyses are conducted on the data in order to address the research questions and to find interesting insights. Most notably, the returns on and around revisions days are calculated and compared to "normal" returns and changes in volume around revisions are also researched. Later, these are used as a basis to formulate a target price -driven investment strategy, the returns of which are analyzed on different levels and compared to the benchmark and individual stock returns. Lastly, the informativeness of target prices is tested by forecasting stock prices against a benchmark that lacks revision data.

5.1 Target price accuracy

In general, the target price forecasts were optimistic as noted in earlier research, and a 10 per cent premium over the current price was very common. What is also interesting was that only three stocks had an average target price less than the current stock price, i.e. had negative target price implied returns (TPIR), although almost half of the stock returns were negative. This goes to show the optimism of analysts, and that revisions often tend to be premiums over the current stock price, and perhaps analysts are too optimistic about the anticipated market sentiment about stocks. That is, that analysts may set target prices clearly above the value based on fundaments and overestimate the fair price by relying too much on demand-based factors. In an optimal scenario most target prices might be attainable, but as found out here and in earlier studies that is seldom the case. It was noticed in the analysis that some estimators apparently even used purely algorithm-based revisions which occurred more often compared to peers, but their accuracy was poor and the changes in target prices were minor and of little relevance. Especially one estimator, PRMDN003, stood out from this perspective as its revision frequency was very high compared to others, and the revised target prices often differed only nominally from the previous one.

Target price accuracies were calculated for revisions released between January and July of 2018 and compared to actual average prices of the corresponding dates a year ahead. Target prices were only collected from seven months due to lack of corresponding price data for revisions past July 2018, as there was price data only until July 2019. If the target price release date or the respective one-year-ahead date was not a business day, the next business day was used. Also, it was assumed that the target price horizon was 12 months; which was the case for the clear majority of forecasts. The results are consistent with earlier research and indicate that target prices are often optimistic – there were few forecasts that implied a target price less than the then current one and also, the forecasted prices were generally significantly higher than the actual prices in 12 months' time.

There were a total of 41 unique estimators in the data, which had one or multiple analysts, but no research was conducted on the analyst level. During the seven-month timeframe, the number of target prices issued per estimator varied from one to 257, while the average was 24.3. As there were generally only two major information releases, quarterly reports, for each company during the time period, it was not considered necessary to filter out estimators with few revisions.

The average target price was 20.2 % higher than the actual stock price after the forecast horizon, with the median being 21.0 %. Thus, target prices are not nearly accurate enough to be solely used for long-term investment decisions, which has been discovered in earlier research. Only seven out of the 43 estimators had an average target price less than the then current stock price, and the forecasts did not fare any better than their more optimistic counterparts. For estimators with more than equal of 20 forecasts (n=58) the average target price was 28.4 % above the one-year-ahead stock price, hence they performed worse than those with less forecasts. The differences in the numbers of revisions issued can be explained by either that the estimator issues revisions to multiple companies or by the high frequency of revisions. Whichever the reason, estimators with fewer revisions performed better than those with more, somewhat surprisingly.

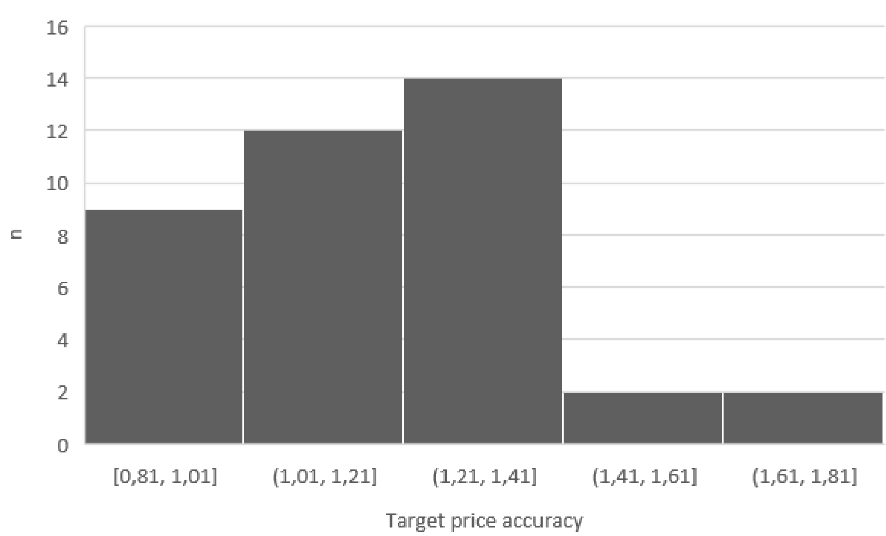


Figure 1. Distribution of target price accuracies among estimators

The clear majority of target prices were above the stock prices in 12 months' time, as seen from Figure 1. This is consistent with the consensus about analyst optimism, although it is noteworthy than nine estimator's mean target prices in relation to the forecast horizon's stock prices were between the 0.81-1.01 range. As mentioned before, due to the poor accuracy of target prices they are not informative enough alone to base long-term investment decisions on.

As discovered, target price accuracy seems to improve when fewer revisions are issued. Less forecasts may lead to better accuracy due to domain knowledge or pure luck. As remarked earlier, target prices suffer from bad accuracy in general and sometimes an educated guess may even yield better results. When there are more forecasts, the difficulty of forecasting will become apparent and successful guesses or forecasts can be outweighed by less fortunate ones. Commerzbank was the only estimator that could reach a perfect accuracy score of 1.00, albeit with only four forecasts for Fortum. The stock was one of the easiest to forecast as the average target price was only 1.4 % higher than the actual share price – a figure much less than for most stocks in the data, which will be covered in more detail later.

5.2 Intra-day returns upon revisions

Table 2: *Daily returns upon revisions and mean TPIR*

	daily return	TPIR
CGCBV	0,993	0,17
ELISA	0,999	-0,02
FORTUM	1,002	0,07
HUH1V	1,006	0,1
KCR	0,995	0,33
KEMIRA	0,998	0,09
KESKOB	1	0,33
KNEBV	1,002	-0,01
KOJAMO	0,998	0,18
METSB	0,996	0,13
NESTE	1,007	-0,04
NOKIA	1,002	0,19
ORNBV	0,986	0,07
OUT1V	0,988	0,17
SAMPO	0,997	0,11
STERV	0,999	0,18
TIETO	0,992	0,05
TYRES	1,001	0,16
UPM	1,001	0,12
VALMT	0,997	0,06
WRT1V	0,997	0,12

The table above shows the comparison between average intra-day stock price shifts and implied returns of target price revisions, i.e. a comparison between the current stock price and target price. There seem to be very little correlation between the two, and thus target prices, on average, don't seem to affect intra-day stock prices. It is especially noteworthy that the magnitude, or the scale of change, of target price implied returns have little influence on returns. The correlation between the two figures is actually negative, -0.19, which isn't surprising given the great difference between the returns and implied returns. The daily return is only calculated for dates on which a target price revision was published, and it is the difference between the closing and starting price. The low correlation is an interesting discovery that shows that on the average, a target price -based trading strategy should not be viable per se. The finding leads to more questions about the possible differences between estimators and whether target prices would result in higher returns some days after the initial release. These questions will be addressed later. The negative correlation is explained mostly by the fact that implied returns do not drive actual returns, but it was concluded that there could be value in the signal.

5.3 Stock returns and target price accuracies

Table 3: Stock-level target price accuracy data

Ticker	Mean TP	Price in 12 months	tp_acc	Stock return
CGCBV	49.84	33.49	0.51	0.58
ELISA	35.30	38.88	-0.09	1.30
FORTUM	19.76	19.52	0.01	1.27
HUH1V	35.46	33.96	0.05	0.99
KCR	44.54	32.42	0.39	0.70
KEMIRA	12.61	12.12	0.04	1.17
KESKOB	48.04	38.64	0.24	1.20
KNEBV	44.20	46.67	-0.05	1.16
METSB	8.68	5.48	0.63	0.56
NESTE	18.17	29.34	-0.38	1.69
NOKIA	5.54	4.97	0.12	1.26
ORNBV	30.80	31.07	-0.01	0.98
OUT1V	7.18	3.40	1.12	0.32
SAMPO	47.85	40.90	0.17	0.82
STERV	16.36	11.28	0.46	0.78
TIETO	29.00	23.93	0.21	0.88
UPM	30.13	25.35	0.19	0.95
VALMT	18.52	21.48	-0.12	1.07
WRT1V	19.33	13.68	0.42	0.65

Table 3 shows means for target prices, their accuracies and for stock prices, in addition to stock returns. The target price data is from January-July of 2018 while the actual stock prices and respective target price accuracies are from the same period of the following year. The *tp_acc* column shows the relation between the mean revision values and actual stock prices from the same time period in 2018 & 2019, respectively. The stock return is from the full time period of 19 months and is included as a reference for comparing it with target price accuracy – in general, the more volatile the stock has been the more off the target price accuracy tends to be. It is noteworthy that Kojamo (KOJAMO) and Nokian Renkaat (TYRES) are not included in the table as Kojamo wasn't part of OMXH25 in 2018 and the latter doesn't have target prices for 2018 in I/B/E/S.

In general, Table 3 shows a correlation between stock returns and target price accuracies. This is natural, as it is easier to forecast target prices for stocks that see no major changes in fundamentals and have relatively steady price changes as opposed to ones with major changes to business environments and competitive positions. The rather naïve forecast models often in use, such as earnings multiples, also support forecast accuracy in cases where the future stock price is similar to the recent (Da, Hong & Lee, 2016). Conversely, perhaps optimistic revisions might affect stock price development too. A stock's good momentum might be fueled by optimistic target prices, leading to higher prices and revisions.

What is noteworthy is that analysts seem to be unable to foresee very positive stock price developments as in the cases of NESTE, ELISA and FORTUM, as one could argue that the drivers for positive returns were already at place when target prices were calculated. So, despite the fact that analysts seem to be overly optimistic about target prices, as a whole, they seem to be unable to capture truly positive drivers in their estimations. For Outokumpu (OUT1V), target price forecasting is always tricky as the business is highly dependent on stainless steel and raw material prices which explains the major difference between target price implied returns and actual returns. Metsä Board (METSB) and Cargotec (CGRBV) are still far away from their 2018 target prices which shows that analysts might have failed to see and capture the major changes to their operating environments when making the forecasts.

5.4 Three-day window returns

Table 4: Average target price changes and three-day window returns around them

	prior	next	return	TPIR
CGCBV	37.45	36.97	-0.01	0.17
ELISA	37.23	37.05	-0.00	-0.02
FORTUM	19.49	19.52	0.00	0.07
HUH1V	30.77	31.06	0.01	0.10
KCR	32.07	31.85	-0.00	0.34
KEMIRA	11.38	11.35	-0.00	0.09
KESKOB	37.18	37.12	-0.00	0.33
KNEBV	44.94	45.06	0.00	-0.01
KOJAMO	10.33	10.43	0.01	0.18
METSB	7.10	7.10	-0.00	0.12
NESTE	24.75	25.09	0.02	-0.05
NOKIA	4.83	4.84	0.00	0.19
ORNBV	28.81	28.36	-0.01	0.07
OUT1V	4.67	4.58	-0.02	0.17
SAMPO	42.83	42.71	-0.00	0.11
STERV	12.84	12.94	0.01	0.18
TIETO	25.84	25.73	-0.00	0.05
TYRES	27.41	27.57	0.01	0.15
UPM	27.50	27.58	0.00	0.12
VALMT	19.95	19.91	-0.00	0.06
WRT1V	15.68	15.68	0.00	0.12

Table 4 shows the return from the day prior to the following day around revisions, i.e. the three-day window returns. The target price change is calculated as a division between it and the release date's average stock price. The story is much alike as in intra-day returns – there seem to not be a strong correlation between target price releases and returns from the surrounding days in the sense that high TPIR does not yield high returns. Thus, it seems that the market is functioning efficiently and does not overreact to target price revisions in aggregate. There seem to be some strong reactions around target price revision days, but they do not seem to correlate with the direction of the revisions, for instance in the cases of Orion (ORNBV) and Outokumpu (OUT1V). Both stocks saw strong negative returns around revisions, even though both had comfortably positive TPIRs on average. In Orion's case, it could be argued that investors were disappointed in the small upside, but the same cannot be said about Outokumpu. Hence, it is expected that the target prices are not the most important driver that affects returns around revisions as the returns are not consistent across the data. The differences between reactions to revisions called for more analysis, which was conducted on the estimator level and helped explain some of the inconsistencies. It is still noteworthy that even a small price change driven by a revision can add up to abnormal returns when there are multiple revisions in a week or month. This was observed later on in the investment strategy part, where the number of transactions was relatively high but so were the returns.

What is interesting about the results is that in many cases there were multiple target prices announced on the same day, most often shortly after earnings announcements. Sometimes, there was a lot of variation between the target prices and the stock return didn't correlate with the majority of target prices, e.g. if most target prices were negative, the return could still be positive. Thus, the assumption is that in those cases, either the investors react differently to revisions by different estimators or there was some unobserved factor that affected returns. For the most part, though, the highest returns were driven by positive target price implied returns but the same cannot be said for the highest negative returns, which incurred even if implied returns were comfortably positive.

There was weak correlation between the highest TPIRs and realized returns, further validating the assumption that high implied returns do not necessarily drive high returns. The highest returns were mostly achieved on days when there were multiple revisions announced, but as mentioned earlier the revisions were often mixed. Due to these findings, it was decided to test whether the estimator plays a key role in the market's reaction to revisions, which is covered in detail later.

5.5 Correlations between TPIR and returns

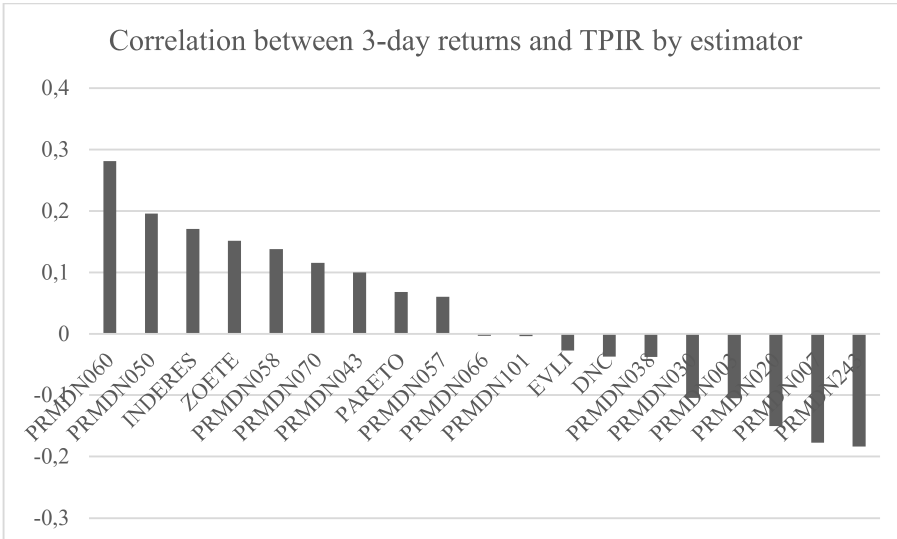


Figure 2. Correlations between next-day returns and TPIR

Figure 2 shows the correlations between three-day window returns and TPIR for estimators with more than 30 target price revisions across the 19-month horizon of the data. 30 was chosen as the limit to negate possible coincidences caused by a small number of revisions, but on the other hand it was not taken into account for how many stocks the estimators were giving target price revisions to.

It is evident from Figure 2 that there are significant differences between the estimators in terms of correlations between TPIRs (target price implied return) and actual returns. From the perspective of a private investor, utilizing target price revisions for short-term trading seems to have some value, but it is important to consider that there are differences in market reactions to revisions depending on the estimator. By reacting according to TPIR to revisions by estimators with positive correlations with returns, one could perhaps be able to reach abnormal returns compared to normal stock price development. This works vice versa too; if an investor reacts to revisions by the "wrong" estimators, the returns will most likely be more negative than a random guess.

Although it is out of the scope of this thesis to examine which factors cause the relatively large variance between correlations of TPIR and returns of different estimators, there are some general ones that most likely explain at least a part of it. Reputation, track record, activity, visibility and presence are examples of these factors. Good quality earnings- or target price forecasts fuel good reputation and track record and increase the credibility of the estimator. Being present in forums and social media and being active in terms of content creation also help increase the visibility of the company. Also, traders and trading algorithms might be able to recognize the higher impacts of some estimators which they could utilize in reaching higher returns, further increasing trade volume and returns around revisions by specific estimators. Thus, it is difficult to judge whether the differences in Figure 2 are due to the revisions themselves, or because of traders who actively try to take advantage of increased volumes around the revisions. The change in turnovers will be covered later on, as it seems to grow significantly around target price revisions compared to the annual average.

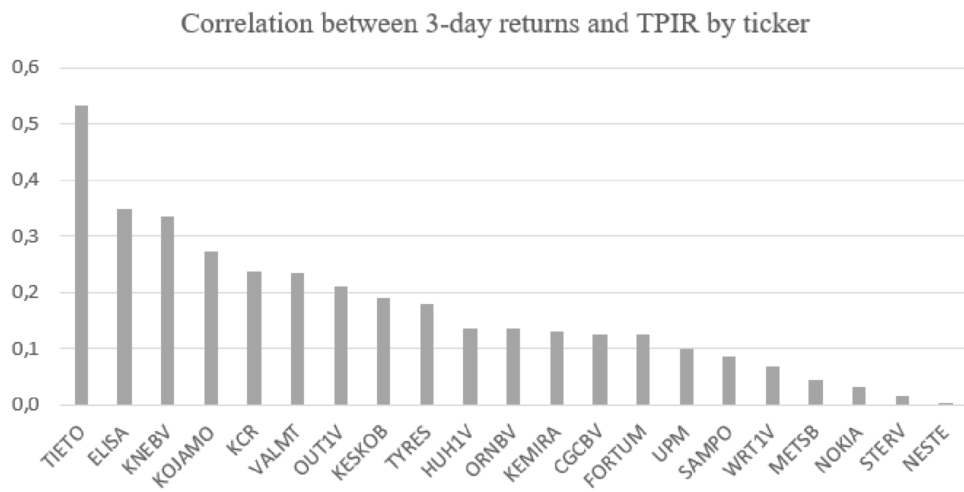


Figure 3. 3-day window return and TPIR correlation by ticker

Figure 3 above shows the correlation between the same variables as Figure 2 earlier but on the ticker level. Unlike on the estimator level, all correlations are positive and range from NESTE's 0.000805% to TIETO's 53.4 %. The mean, non-weighted, correlation is 0.17, which is not that high but considering that there are no negative values, the scores in general are decent. Keeping in mind that the daily and three-day returns are typically much lower than TPIR values, the correlations are relatively high. Perhaps by scaling the values the scores would be higher, but even using the actual values shows that revisions influence next-day stock returns. Still, there is less variance on the company-level than on the estimator-level, reinforcing the finding that reactions to revisions not only depend on TPIR, but also on the issuer.

The findings plotted in Figure 3 provides investors with very basic-level information about market reactions to revisions at the company level, which could be utilized very easily. An investor can be fairly confident that TIETO and ELISA stock prices react more consistently to TPIRs than the ones of STERV and NESTE. Even when utilizing estimator-level data, it should be considered how stocks differ in reacting to revisions. Throughout the analysis it has become apparent that it is often not viable to neglect any of the multiple factors relating to revisions and their stock price implications, as there are differences between companies, estimators, TPIRs and market situations.

5.6 Returns comparison

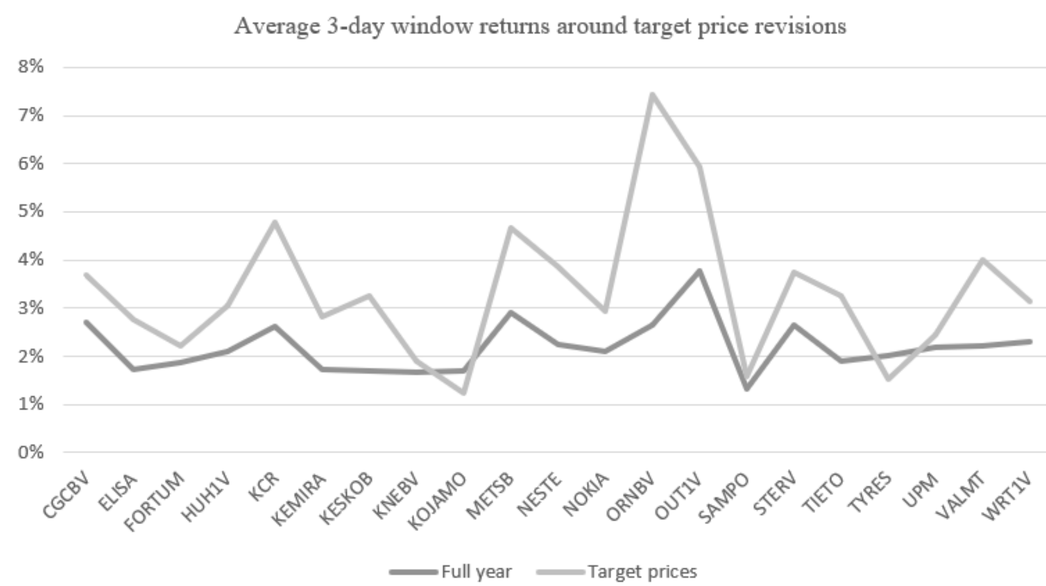


Figure 4. Absolute mean returns around revisions and normal days

Figure 4 above shows the average three-day window returns around target prices and normal three-day returns from the entire dataset per stock. There is a clear deviation from normal returns around target price revisions for most stocks, especially for the most volatile stocks KCR, ORNBV and OUT1V. The average returns calculated in the table use absolute values, thus the table is only useful for illustrative purposes. Nevertheless, the figure shows that target price revisions cause significant market reactions which investors could use for their advantage – if they are able to figure out the direction of the stock price. As noted earlier, TPIR does not correlate much with actual returns and the market reaction is often volatile in regard to TPIR reactions, making it hard to foresee whether the reaction is positive or negative. This is partly due to differing reactions depending on the estimator, but sometimes even the best estimator cannot dictate the revision day returns.

There are only two stocks, KOJAMO and TYRES, for which the returns around target prices are less than the normal ones, which might be due to them having only 21 and 17 revisions available, respectively. For others, except SAMPO, the absolute mean returns are notably higher around target prices, which contradicts with the efficient market hypothesis as target prices are based on information that is already available. Studies suggest that target prices carry information about discount rates, alongside about future earnings and risks, but they are also included in earnings forecasts (Han & Kim, 2019). Perhaps the increased stock turnover around target prices encourages traders to take positions upon revisions, which further increases volatility and trade. Whichever the reason behind the volatility surrounding revisions, it is interesting to see how big the impact is.

The three-day window return here is calculated using the opening price of the prior day of the revision, and thus the return is not what investors can actually achieve as estimators rarely announce revisions in advance. Figure 4 just shows the returns deviation between normal- and revision days. The potential returns by utilizing target price revisions will be covered later on in the thesis. The more volatile returns lead to the assumption that the stocks' turnover must see increases around revisions, which will be looked into next.

5.7 Turnover

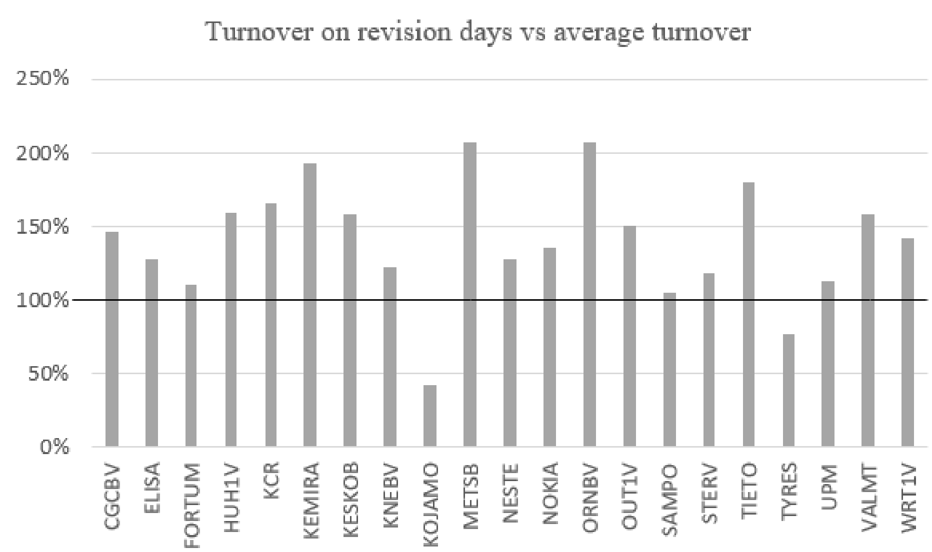


Figure 5. Relation of stock turnover on revision days compared to the average

Figure 5 shows the change in stock turnover on target price revisions days compared to the average turnover throughout the dataset. Only two stocks, KOJAMO and TYRES, show less than double the turnover upon revisions than during the average day. The two stocks have shown anomalies in other aspects as well, since for instance there's only two months of revision data for TYRES, but with the data available it is hard to say if it is to blame, or if they actually behave very differently compared to other OMXH25 stocks.

In general, the effect of target price revisions is significant for stock turnover. The mean turnover on revision days is 140 per cent higher than on a regular day. Thus, the market reacts strongly to target prices, even though they are based on information that is already available, making the reaction somewhat questionable. Nevertheless, the market clearly sees value in target prices, whether it be in terms of informativeness or in a chance to make quick profits due to increased trade. METSB and ORNBV see the stock turnover triple, on average, upon target price revisions which is also reflected on the returns. KCR's absolute returns were also much higher on revisions days, but the turnover is only slightly higher than the average turnover increase and far behind the trade fluctuations of METSB and ORNBV. In general, the deviations in returns and turnover go hand to hand, but it is difficult to say which causes the other. Are stocks purchased after target price revisions because the price is anticipated to drift into the direction suggested by TPIR, or do traders take positions in stocks in anticipation of more turnover and volatility?

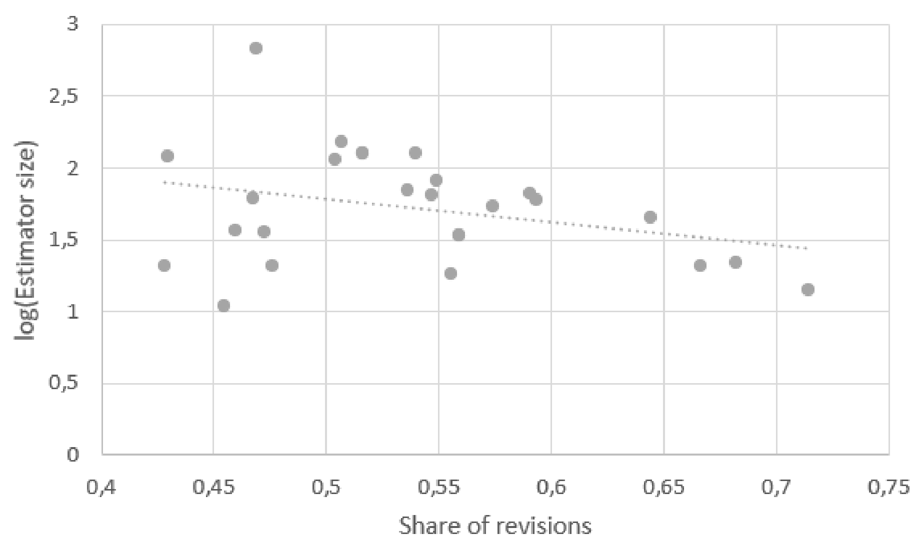


Figure 6. Share of revisions that share same-signed TPIR and next-day returns

Figure 6 shows the distribution of revisions and next-day returns which share the same sign by estimator size; with same sign meaning that for instance, if the TPIR is negative the next-day return is also negative and vice versa. This was conducted due to the finding that the scale of TPIR showed little correlation with actual returns, implying that the signal is more important than the revision value. The number of revisions is used to capture the estimator size, and Figure 6 shows the logarithm of that number to facilitate comparability, as the revisions range from 11 to 678. Estimators with less than 10 revisions were not included in the figure.

The figure is rather relevant in terms of this thesis as one of the research goals is to find out whether target price revisions yield consistent market reactions which could be useful for investors. The best estimator was capable of affecting next day returns 71 % of the time, but it only had 14 revisions for several companies and thus good fortune can play an important role in such a high "success rate". The trendline shows that the higher the number of revisions, the lower the chance of TPIR positively correlating with the next day return. The data reveals that for estimators with more than 60 revisions, this share is 51 % while it is 57 % for those with less than 60 revisions across the dataset. Thus, it does not seem like there are major, though observable, differences between estimator sizes in terms of affecting next day returns, albeit Figure 6 does not take into account the magnitude of TPIR or market reaction – which could potentially vary between estimators and result in high returns in some cases. Figure 6 only shows whether the realized next-day return is in line with TPIR; whether they're both positive or negative or whether they differ. Some estimators might cause higher price reactions than others, which yields higher returns, but this cannot be observed from the figure. As mentioned earlier, calculating the correlation between next-day returns and TPIR is also somewhat troublesome, as the returns are generally much lower than the implied return; which also affects the correlation between the two. The magnitude of TPIR and next day return will be covered later in more detail.

5.8 Investment strategy returns

Table 5: 19-month returns using a €1000 investment per revision

	tp recommended	2%	frequency	return per transaction	difference
OUT1V	-761,2	-1335,4	221	-0,0060	75%
ORNBV	298,2	107,6	46	0,0023	64%
WRT1V	1312,9	891,9	197	0,0045	32%
ELISA	1727,1	1577	150	0,0105	9%
NOKIA	813,6	759,2	211	0,0036	7%
FORTUM	307,2	295,6	167	0,0018	4%
CGCBV	-406,9	-415,6	72	-0,0058	2%
STERV	1272,2	1259,7	108	0,0117	1%
HUH1V	795,4	795,4	53	0,0150	0%
KESKOB	-71,7	-71,7	48	-0,0015	0%
KOJAMO	141	141	15	0,0094	0%
TIETO	349,8	349,8	26	0,0135	0%
TYRES	29,1	29,1	5	0,0058	0%
SAMPO	-321,8	-309,1	158	-0,0020	-4%
KNEBV	839	896,6	192	0,0047	-7%
UPM	365,1	435	165	0,0026	-19%
METSB	251,4	305,4	73	0,0042	-21%
KEMIRA	100,4	147	28	0,0053	-46%
KCR	-123,3	-0,9	58	0,0000	-99%
NESTE	-272,9	417,4	214	0,0020	-253%
VALMT	61,8	247,2	62	0,0040	-300%

Table 5 compares the outcomes of the revisions-driven investment strategy, where a position was taken based on the TPIR suggestion upon each revision. Transaction costs were not included in this comparison, but will be addressed in later chapters, as the focus here is to solely examine the viability of the strategy. The table also shows the mean return per transaction and the quantity of transactions/revisions.

Table 5 shows the aggregate returns from the whole 19-month dataset when using a €1000 investment upon target price revision; with the assumption that the stock is sold the following day at the closing price. The *tp recommended* column shows the returns by using a logic where negative target price implied returns (TPIR) are used as a signal to short the stock, while all positive TPIRs are interpreted as buy signals. The *2 %* column, on the other hand, utilizes a condition where TPIRs greater than -2 % are used as buy signals. The aggregate profits for *tp recommended* and *2 %* are €6706.4 and €6522.2, respectively.

The *difference* column shows the difference between the other two columns, with positive values meaning that the *tp recommended* return is higher than *2 %* and vice versa.

Although the *tp recommended* yields higher aggregate returns than *2 %*, there are significant differences between the two at stock level. Only on one instance does *2 %* yield higher losses than *tp recommended*, albeit it being the biggest loss of all, OUT1V, but in general it seems to be more robust to countering losses. But as mentioned, *tp recommended* reaches the higher total profit and is able to capture more profits from winning stocks. Based on the results shown in Table 4, the TPIR-based investment strategy is not viable for all stocks as it might result in sizable losses, but for the majority of the stocks it seems viable. Before using this strategy, an investor should consider the clear differences in how stocks react to target price revisions, as for some a small negative TPIR can still result in a stock price hike the next day, but for other stocks the reaction could be the opposite.

2 % was chosen as the threshold for tolerating negative TPIRs due to higher deviations between returns and lower aggregate returns at higher rates, while results with lower rates were too similar to the benchmark ones. The reasoning to look into whether results would vary if some negative TPIRs were considered as buy signals stemmed from the high variation between results while using the default logic. It was evident from the data that especially for stocks with stable stock prices, minor negative TPIRs did not seem to correlate much with next day returns. NESTE was the only stock that went from a negative return to positive by using >= -2 % TPIRs as buy signals and by a major difference. NESTE is an odd stock in the sense that its stock return during the 19-month timeframe was sizable, and target prices were too conservative to capture its potential. Still, it is interesting how the market reacted so positively to conservative revisions; behavior which could not be observed in other stocks. NESTE clearly had a great momentum going on during the entire timeframe, but it is still remarkable how it consistently achieved such high next day returns despite conservative TPIRs. In NESTE's case, it is perhaps not advisable to follow the target price -based investment strategy as analysts have not been able to capture the stock's potential in their forecasts.

Five stocks did not see any change between *tp recommended* and *2 %* as they did not have negative TPIRs higher than -2 %. Overall, there were 2269 revisions in the data used for Table 5, excluding TELIA1 and some dates that were not recognized as business days by the US calendar. Of the 2269 revisions, only 27 % were negative while out of three-day returns, half were negative. This remark was one of the reasons why it was tested whether some TPIRs could be considered positive as there was a clear contradiction between actual returns and revision signals. It was also tested whether small positive TPIRs could be used as short signals, but the results were worse overall than the benchmark method or the -2 % one. There were some exceptions, but they were relatively insignificant.

All in all, utilizing the target price revision -based investment strategy is profitable, but there are sizable differences between stocks in terms of returns and thus the viability of the approach. As for some stocks the use of small negative TPIRs as buy signals yielded positive returns the next day, it cannot be stated that revisions solely could be used as a basis for an investment strategy due to differences between the returns. An investor should look into how a given stock reacts to different revisions in general, and then consider whether they could be used as a signal to trade. For some stocks the returns were comfortably positive, but for some even the best approach resulted in losses. Thus, it is very case-depended what kind of returns this approach can yield, and whether they are positive or negative. In chapter 5.11 a similar comparison to Table 5 is conducted on the estimator level, and the revision-based investment strategy will be benchmarked against the OMXH25 index later.

A €1000 investment was chosen to be used instead of showing pure returns in aggregate due to the nature of the strategy – individual transactions yield such low returns that a relatively high investment is required to achieve meaningful returns, as seen from the table. Even though there might be high individual returns, the mean returns are of small scale and thus volume is required to rack up profits. The 2 % approach is used in the following graphs and figures, despite it generating a lower aggregate profit than the intuitive approach. This is because the 2 % rule did better in the majority of the cases; its lower returns were due to it performing worse in both ends of the scale – in the highest and lowest returns. In general, it performed better in capturing the effects of revisions on short-term returns and thus it was selected as the preferred approach.

5.9 Returns comparison

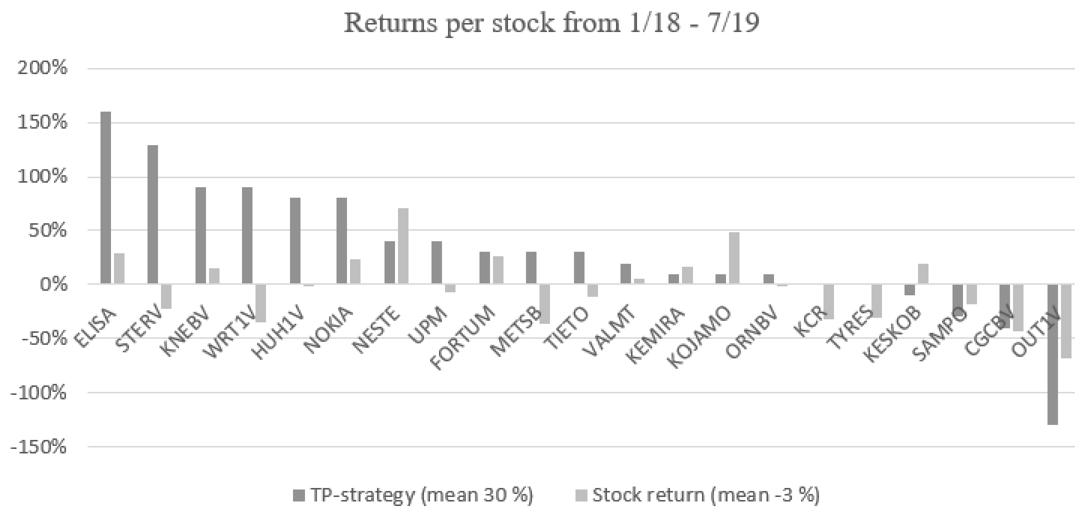


Figure 7. Returns for the revision-based strategy and stocks during the 19-month timeframe

Figure 7 shows the returns of the revision-based strategy and stock returns from the data timeframe, using the 2 % approach. The two differ in the sense that the TPIR-based returns are an aggregate of all individual investments made according to the strategy, while the stock return is a one-time investment from January 2018 to July 2019. More comparisons will be introduced later, Figure 7 just showcases the simplest comparison. It can be seen that the TPIR-strategy is more profitable in general, but as noted earlier, there are differences between stocks. For instance, an investor would have been better off by passively investing in NESTE and KOJAMO than by using the TPIR-approach. But for stocks like ELISA, STERV, WRT1V and NOKIA, the TPIR-strategy is significantly more profitable; especially in the case of WRT1V where the stock return is negative but the TPIR return is almost 100 %. These significant differences mean that the TPIR strategy isn't viable for all stocks, because of losses or simply because holding a stock may yield as much returns even when dividends are excluded. Fortum is a prime example - the difference between the two approaches is only 3 %, and factoring in the added workload and dividends would most likely outweigh the three percentage point deficit.

The mean return for the TPIR-strategy is 30 % while it is -3 % for the 21 stocks. The average annualized returns are respectively 19 % and -1.9 %, while the OMXH25 GI index yielded -4.7 % in 2018 and 9.8 % in 2019. This index does not include dividends, making the comparison more relevant but it also results in lower returns. Dividends are an important factor in terms of returns for passive investors, but for the sake of comparability they were left out in this case. Even if dividends were included in the index, the TPIR strategy returns would still be notably higher. It's noteworthy how much the returns between the index and stocks differ; the former is weighed and the latter is missing four stocks.

OUT1V is an outlier in the sense that its revision-based return exceeds -100 %. This is because the return of the target price approach is calculated as a sum of realized returns from the data, with each investment requiring “new” capital. By following TPIR as a signal for the 221 investments upon revisions, the aggregate return is -130 %. Thus, assuming a fixed investment for each revision, an investor would have lost the investment 2.3 times by the end of 19 months of trading. This figure is an aggregate of all OUT1V returns in relation to the fixed sum invested upon each revision. This highlights the difference between a one-time investment and the trading strategy used here, wherein the prior one can only lose the invested capital at worst, but in the latter the aggregate losses can exceed the fixed investment. By shorting one can also lose more than the invested capital, but not in long positions. Theoretically short losses can be infinite, but here the position is exited the following day, mitigating its risks.

In the calculations, the opening price is the closing price of the day prior to a target price release, because if the target price is released before the Helsinki stock exchange opens, after-hours trading may affect the opening price. After-hours volumes may also be increased due to revisions published outside the trading hours. Thus, the “noise-free” prior closing price is used instead of the opening price of the revision day, although the two prices are often very close to each other.

5.10 TPIR logic returns by estimator

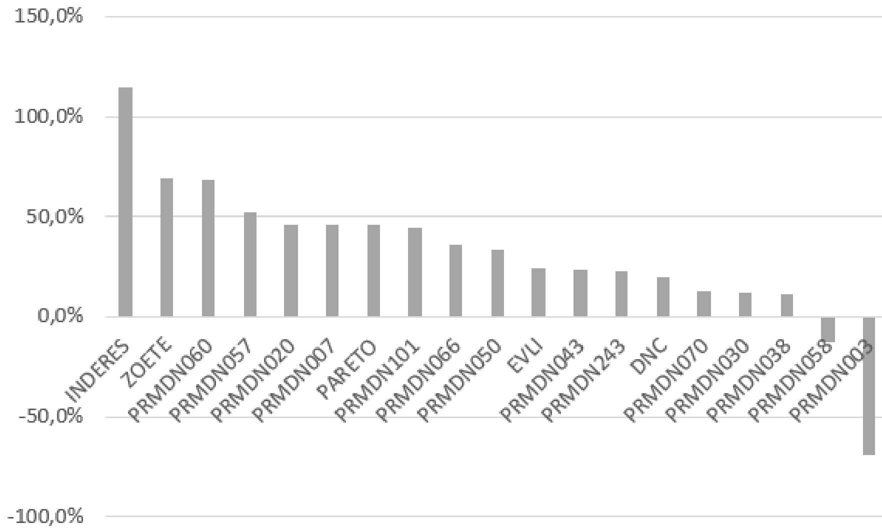


Figure 8. 19-month returns by estimator using the 2 % logic in reacting to revisions

Figure 8 shows the distribution of returns by estimators using the 2 % approach in reacting to revisions, i.e. where >= -2 % TPIRs are considered as buy signals. The figure confirms the assumption that there are significant differences in how the market reacts to revisions by different estimators. PRMDN50, PRMDN060 and INDERES had the highest correlations between TPIR and three-day returns shown in Figure 2, but only the two latter achieved clearly above average returns versus their more mediocre peers as seen from Figure 8. INDERES reached the highest returns by far out of all estimators – the market reaction to most INDERES revisions is easily observable on a daily basis and was perhaps the single most important factor for choosing this as a thesis topic due to the common strong market reaction its revisions spark. In terms of target price accuracy, INDERES is not extraordinary, but the company has a good reputation in generating relevant analyses and recommendations for investors and this positive perception about the company may fuel the strong market reactions to its revisions.

The data was filtered so that only estimators with more than 30 revisions across the dataset were included in Figure 8. This was due to the assumption that too few revisions may result in seemingly high returns or correlation due to coincidence and in order to avoid cluttering the figure too much. The revision count varied from 34 to 678. Interestingly, PRMDN003 had the highest number of revisions but also the worst return. Looking closer at these revisions, it seems like there might be some sort of algorithm generating the revisions as the estimator often issues multiple revisions for one stock per month, which is not unique but rather unusual. The typical approach seems to be to revise target prices when important information is released on the market, often after earnings announcements or major stock exchange releases. The mean target price accuracy for PRMDN003 was 0.18, i.e. the target price was 18 % higher than the stock price after 12 months which is actually an impressive number, given that for instance INDERES' one was 0.22. Thus, the contradictory market reaction to TPIR is not explained by poor accuracy, but perhaps the sheer number of revisions is enough for investors to not consider PRMDN003's revisions as relevant information. Furthermore, many of the revisions were very conservative; explaining the high target price accuracy and the poor market reaction as the revisions rarely offer surprising signals. As the name is masked, it is not known whether the estimator provides a report alongside the revision, as most others do, which could be utilized by investors to gain insight. This probably is not the case due to the high number of revisions and could explain the lackluster market reaction, as investors might want to be able to understand the drivers of a target price instead of just seeing the number.

Again, it seems that if an investor is able to identify the most successful estimators, high returns can be achieved by following the target price -driven investment strategy. This was also the case with the same analysis using companies instead of the estimators – the approach is also profitable as a whole but there is high dispersion in returns between the stocks and estimators. In INDERES' case, 115 revisions yield on average 1 % return each, which is impressive for a two-day return – from the revision day to the next one. The OMXH25GI dividend-free index yielded 9.8 % from January to July in 2019, thus investing in 10 INDERES revisions should have achieved the same return on average, excluding transaction costs. Obviously, there are differences in the return depending on the company and its current momentum and how the stock market as a whole is doing at the moment, but still the target price -driven approach should be comfortably profitable if used correctly. As most of the OMXH25 stocks' marked capitalizations are relatively small compared to many European or US ones, they can exhibit more anomalies that can be exploited. The same goes for the entire index; it has been observed that small and medium cap stocks have yielded 0 % returns from May to September during the last 10 years (Inderes, 2020) and some OMXH25 stocks fall into the medium cap class. Thus, it is evident that anomalies exist in the Helsinki stock exchange and that the TPIR strategy may not be as useful in other markets as it seems to be in Finland.

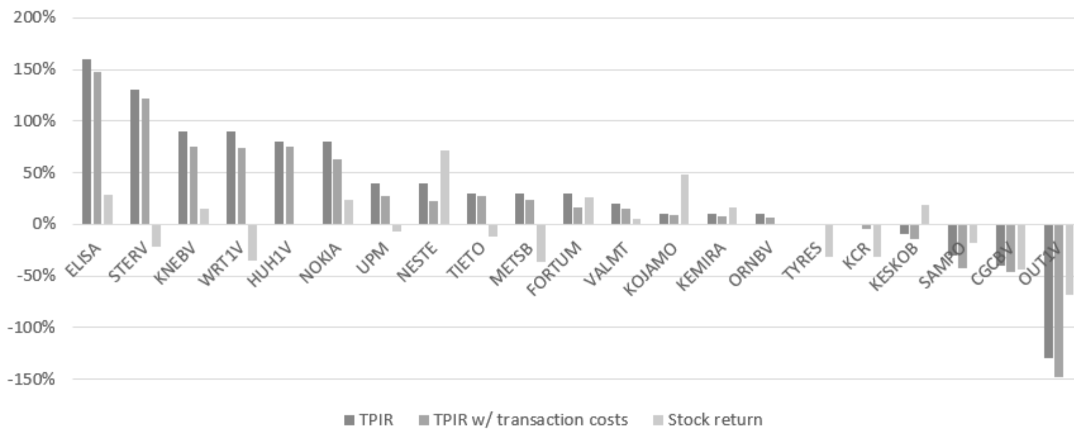


Figure 9. Returns comparison including transaction costs

Figure 9 shows the same results as Figure 8 earlier but also includes transaction costs for the revision-based returns. The stock returns do not include transaction costs, as they are rather irrelevant in a one-time investment when compared to a trading strategy. As mentioned earlier, the transaction cost is fixed at 0.04 % and is naturally incurred twice for each revision: during the purchase and sale of a stock or short position. The more detailed transaction costs can be seen in the next table, but they just reflect the number of revisions.

As Figure 9 shows, there are distinctive differences between the returns of the TPIR approach with and without transaction costs, but for the most part they do not make much of a difference when comparing TPIR strategy returns to stock returns. FORTUM is the only stock where the inclusion of transaction costs makes the one-time investment more profitable than TPIR-based trading. Hence, even though the transaction costs are high due to the high number of trades, the returns comfortably overweigh the costs except in FORTUM’s case. Some brokers might offer enticing deals to active traders that could lower the overall transaction costs and especially overnight shorting costs significantly, making the strategy even more viable. Banks and other established institutions typically charge more than smaller, more focused brokers. New services such as Robinhood, where transactions are free, might help bring down transaction costs in the future.

Table 6: Aggregate costs of transactions and mean returns per stock

	costs	n	TPIR yield
CGCBV	5,8%	72	-40%
ELISA	12,0%	150	160%
FORTUM	13,4%	167	30%
HUH1V	4,2%	53	80%
KCR	4,6%	58	0%
KEMIRA	2,2%	28	10%
KESKOB	3,8%	48	-10%
KNEBV	15,4%	192	90%
KOJAMO	1,2%	15	10%
METSB	5,8%	73	30%
NESTE	17,1%	214	40%
NOKIA	16,9%	211	80%
ORNBV	3,7%	46	10%
OUT1V	17,7%	221	-130%
SAMPO	12,6%	158	-30%
STERV	8,6%	108	130%
TIETO	2,1%	26	30%
TYRES	0,4%	5	0%
UPM	13,2%	165	40%
VALMT	5,0%	62	20%
WRT1V	15,8%	197	90%

Table 6 above shows the aggregate transaction costs on the stock level with the respective returns. As the transaction costs are assumed to be fixed at 0.04 % and each revision causes two transactions, the costs are directly proportional to the number of revisions. In terms of returns the costs may have a sizable impact as for instance in the case of NESTE and NOKIA which have a similar amount of transactions, but NESTE's returns are nearly halved after costs are taken into account. The mean cost of the strategy is 8.6 % while the mean return is 30.5 %, and from this perspective the returns comfortably outweigh the costs.

As the number of transactions is relatively high, costs can have a significant impact on the returns and viability of the TPIR strategy. This also highlights the importance of conducting research into which stocks and estimators should be focused on using this strategy, as not only do some exhibit negative returns but also, the returns may not differ significantly from stock- or index level returns after costs are included.

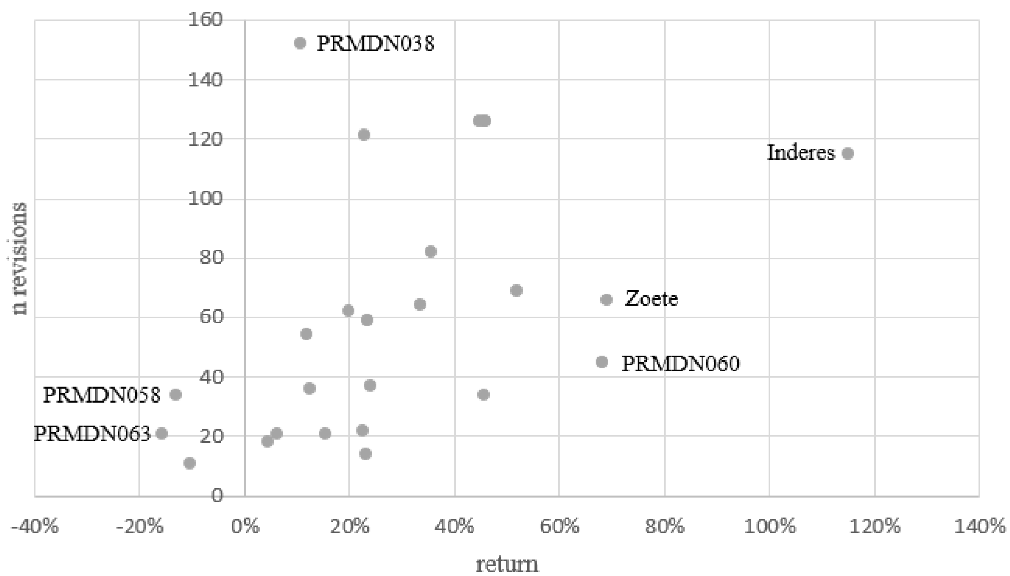


Figure 10. 2 % rule returns by estimator

Figure 10 shows the distribution between the 2 % -based investment strategy returns by estimator size, which is determined by the number of revisions issued. The return is a sum of all transactions based on the revisions issued by an estimator. Figure 10 showcases how the number of revisions affects returns – generally, the revision quantity does not seem to correlate highly with returns. As found out earlier, the market reaction to revisions is seldom consistent and thus a high number of revisions does not guarantee higher returns. The plot excludes estimators with less than 10 revisions across the dataset and estimator PRMDN003, which had the highest number of revisions at 678, with an aggregate return of -69 %. The aforementioned estimator was omitted since its high number of revisions made it difficult to interpret the plot.

There are significant differences between the reactions to revisions depending on the estimator, and also in the estimators' target price accuracies. The scatterplot clearly shows the high variance in returns between estimators, while there seem to be no clear correlation between the number of revisions and returns. The highest return is achieved by Inderes and no other estimator comes even close to its 115 % return, with Zoete achieving the second-highest returns by only reaching 69 %. The mean return and number of revisions were 29 % and 61, respectively, while the weighted average return was 38 %. This indicates that a higher number of revisions yields higher returns theoretically, but as mentioned there is no consistent pattern that would confirm it. The numbers exclude the previously mentioned estimators, as PRMDN003 especially would have a significant negative impact on the mean values.

There are only three estimators that yield negative returns of which all have relatively few revisions, although there are examples of estimators that reach comfortably positive returns with similar amounts of revisions. This goes to show that investors should pay attention to which estimators' TPIRs they should follow as some result in clearly abnormal returns while others may even lead to losses. It should be kept in mind that as shown earlier, the scale of TPIR itself does not have much to do with the next-day returns; it is more important whether TPIR is positive or negative. This is good news for investors as, on the average, only checking the relation between the newly-released target price and current stock price is sufficient to decide which position to take. Thus, for instance, it is not necessary to analyze whether the implied return would be enough for a specific stock to yield returns in a short-term position. This was brought up by an Inderes analyst during an inquiry about target prices; he pointed out that stock recommendation changes are often more important than target price revisions (Inderes, 2020).

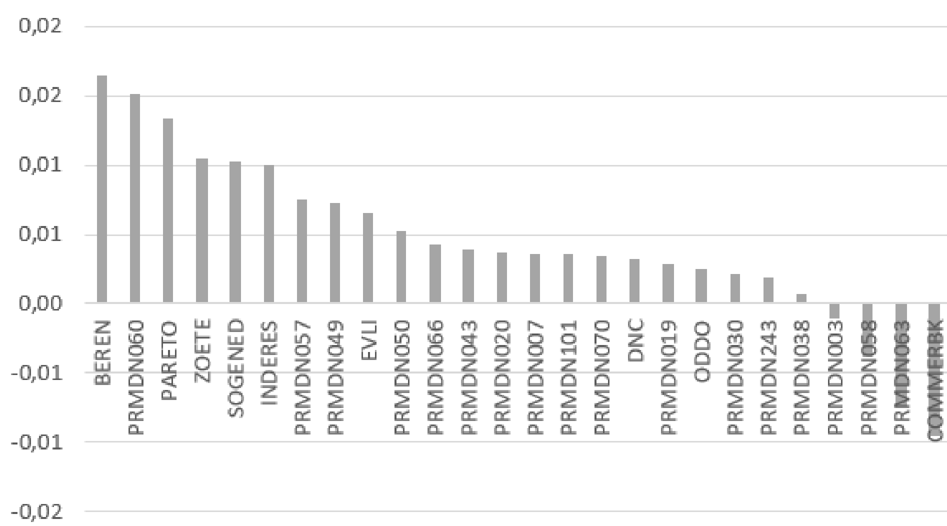


Figure 11. Mean returns by estimator

Figure 11 shows the mean return by estimator using the 2 % investment strategy across all stocks the estimator issued revisions to. Compared to the previous plot, this eliminates the effect of the number of revisions on return. For instance, Inderes performed the best in the aggregate comparison, but here its return is not the highest. Beren only had 14 revisions in the 19-month dataset, but the highest mean return meant that it reached almost 23 % in total in next-day returns despite the low number of revisions. Again, this goes to show that the differences between estimators are high.

Generally, it is noteworthy that it is possible to reach positive returns based on revisions and their implied returns. This is good news for investors but in terms of the efficiency of the Helsinki stock exchange it is questionable. Revisions are based on widely available information and data, and the finding that they cause stock price changes to the extent shown in Figure 11 shows that new information is poorly reflected on stock prices upon release. Although the efficient market hypothesis and perfect markets are purely theoretical and don't actually exist in any stock exchange, it's surprising how big of an effect revisions have on stock returns in the Helsinki stock exchange.

What is peculiar is the fact that there are four estimators that consistently yield negative next-day returns, which is either due to bad timing or extraordinary target price values. PRMDN063 issued over 600 revisions in 19 months and one can wonder what is the point in such a high revision quantity when the mean return is negative. As mentioned earlier, the revisions of this estimator seem to be generated solely by an algorithm due to the high announcement frequency and minimal changes in values, but their informativeness to an investor is minimal and even harmful which makes the practice questionable. In the literature review section, it was noted that target price accuracies are low in general and the main reasons for it were implied to be the lack of incentives and regulation. Thus, these may be the reasons behind the revisions whose TPIRs consistently conflict with market reactions. On the other hand, the rationales, drivers and assumptions behind these revisions may also be justified, but the market reactions just are not optimal. Whichever the reasons behind the sub-optimal relation between some estimators' TPIRs and short-term stock returns, poor performance in this aspect may be hurtful for the estimators' brand and credibility.

The average next-day return for all estimators was 0.0045 and there were six estimators which had at least double that, as seen from the column chart. This doesn't take into account for how many stocks there had been revisions for, or how the revisions were distributed among multiple stocks, i.e. the share of revisions for a single stock is unknown. For instance, if a well-performing stock got a disproportionately high share of revisions, this is positively reflected on the estimator's performance. The number of revisions for a single stock was left out of this analysis due to the earlier finding that it is not that relevant – other aspects seem to drive returns more. Variation between estimators in this regard was also generally low, as revisions occur typically after earnings announcements or other major stock releases, which limits the frequency of justified revisions.

Furthermore, it was not considered whether other revisions were announced on the same day for the same stock. This is because there are so many estimators and over 20 stocks, which makes this kind of analysis quite complex and thus it was not conducted. In the next subchapter it becomes obvious that revisions do take place on the same day quite often, typically after earnings announcements, and this impacts the returns of TPIR-based investments. It seems, though, that the market reactions tend to follow the estimators with a good "track record", i.e. the ones that did best in Figure 11, and thus multiple revision days shouldn't need to be avoided by investors for the fear of inconsistent price developments. It just has to be kept in mind that price reactions typically seem to follow certain estimators and not e.g. the consensus of a specific day.

All in all, the results shown in Figure 11 provide strong evidence that stock prices are impacted by target price revisions and signal that the Helsinki stock exchange does not live up to the efficient market hypothesis. The author believes that despite there being data from only 19 months, the results can be generalized as the chance of achieving comfortably positive returns by following revisions across the dataset is high, particularly if some guidelines are followed. The correlations between next-day returns and TPIR are somewhat low most likely due to the fact that the stocks don't reach as high returns as TPIR indicates, similar to what has been observed in the post-earnings-announcement drift phenomenon and because target prices are often only for reference and inaccurate. The signal, to buy or sell, seems to be more relevant to investors while the return potential is less important, at least when the largest OMXH stocks are concerned. Perhaps analyst insights are more valuable for smaller stocks in terms of realizing hidden potential, but in larger stocks the biggest benefit of target prices seems to lie in their implications to short-term price development.

5.11 Differences in returns by ticker and estimator

As made evident by the previous results, the returns depend notably whether the tickers or estimators are used as the approach for calculations. Investments by following TPIRs in ELISA or STERV exceed the returns of the most well-performing estimator, INDERES – implying that estimators are less consistent in generating returns based on revisions. This indicates that stocks are more robust to changes in TPIR-based returns, even though there are sizable differences among estimators as well.

On the ticker level, TPIR shared the same sign with the next-day return 57.3 % of the time, while on the estimator level the success rate was 54.5 %. The correlation between the mean next-day returns and the share of successful “predictions”, i.e. TPIR and return sharing the same sign, about next-day returns was 0.52 and 0.75 on the ticker and estimator lever, respectively. On the other hand, when estimators are filtered so that only those with 30 or more revisions issued are concerned, the correlation decreased to only 0.54. This implies that the speculation about luck being a relevant factor in explaining high TPIR-based returns with small estimators is most likely true. It would be, however, possible that the small number of revisions is explained by the focus on one or a few companies – but this was not the case here. The average number of revisions issued by an estimator per stock was 5.7, while it was only 2.9 for estimators with less than 30 revisions issued in 19 months. Given the high success rate of the small estimators’ ability to affect next-day returns, the low number of revisions is peculiar. Thus, it is most likely that small estimators are able to reach high individual TPIR-based returns due to luck or coincidence. As found out earlier, multiple revisions take place on the same day regularly and that the returns seem to follow the TPIR of an estimator with a good track record; which can be beneficial for other estimators. If the small estimators exhibit a capability to affect next-day returns without a helping hand, why would the number of revisions issued be so low?

The mean next-day return by estimator was 0.3 %, and for estimators with more than 30 revisions the return was 0.5 %. Even though this difference does not tell much in terms of returns, as investors have the option to go short, it sheds some light on the ability of bigger estimators to affect future returns, as revisions tend to be optimistic.

A conclusion can be drawn from comparison between estimators and stocks that investors should be able to reach higher returns by following the TPIR strategy on the stock level, as the highest returns are achieved on this level and not by following revisions of individual estimators to various stocks. Yet, some estimators do perform clearly better than others in terms of TPIR-based returns among individual stocks. An investor should look into which stocks react to revisions the strongest, and analyze which estimators most likely cause these reactions through their revisions. Thus, being able to reach consistently high returns requires some research, but positive returns should be achievable even by simply picking the best-performing stocks or estimators for the basis of the TPIR-based investment strategy.

6 Stock price predictions and benchmarking for validation

In order to further test the relevance of target price data, a model utilizing the LSTM algorithm was built. The data comprised of the benchmark, which included all the price- and transaction data from the Nasdaq database and the comparison dataset, which also included the target price revision values. The objective was to test whether the inclusion of revision data would increase the stock price forecast accuracy.

Despite efforts, the author was unable to produce good results by combining the Estimator ID and Value variables together, which in practice meant encoding the categorical Estimator IDs and combining the respective revision values to them. The model performance was poor compared to other runs while using this method, which is most likely due to lack of data which resulted in numerous empty data points. The lack of data is explained by the long interval between revisions, as most estimators only revise target prices after earnings announcements or other such important releases by companies. This meant that the model could have dozens of empty variables if no revision was published on a given day, which most likely caused the poor accuracy due to overfitting. Thus, a simpler but more effective way was used – only the target prices were included, but not the estimator. This approach is not optimal, due to differences between estimators, but was deemed good enough due to promising results.

6.1 Model variables

The variables used for the benchmark forecast were the ones found in the NASDAQ prices dataset: bid, ask, opening & closing price, high & low price, average price, total volume, turnover and trades. The comparison forecast adds target price revisions in the form of the value of the target price - but not the estimator. There were over 20 different estimators for all companies involved, thus one-hot encoding them or using some other method was cumbersome and ultimately not beneficial, as there are not that many revisions per estimator. Thus, although there seem to be significant differences between the market reactions to revisions by different estimators, and despite their views and target price accuracies vary, they were not included due to poor model performance. However, the target price values alone provided additional value for the forecast. In STERV’s and

FORTUM's case, the MSE of the forecast was smaller with revision values and narrowly higher with ELISA.

If there were multiple revisions on the same day, the mean value was used as the forecasts would not have been comparable if double-entries were included. Each revision value was stored on its own row, and if there were multiple revisions on the same day for the same stock, there were duplicate price entries for that day. The data was split into training and validation sets on day 350, and as the revision-containing dataset was longer than the benchmark, this would have resulted that day to be on a different date than in the benchmark data. This was addressed by using the mean revision value on multiple-revision days.

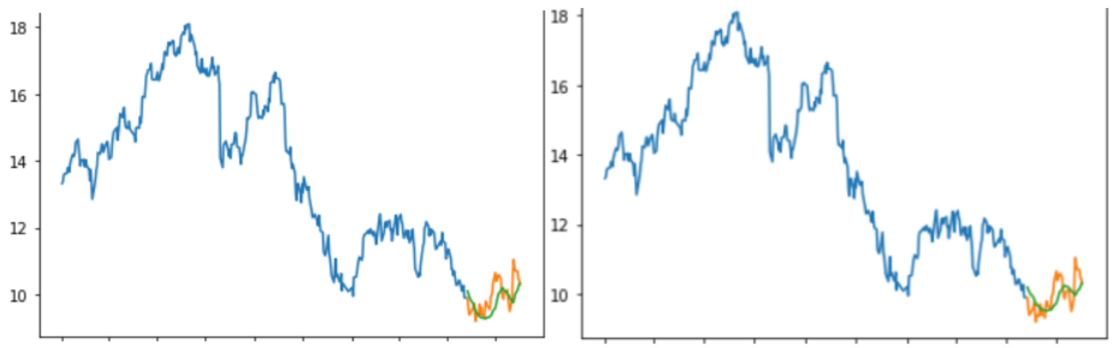
As in earlier in the analysis, revisions announced on weekends or holidays were shifted to the nearest business day. As there were not nearly enough revisions for all trading days, this was relevant and also, the corresponding returns should take place during the next trading day. However, if there were multiple revisions e.g. during a weekend, they all would be shifted to the same day and the mean value of the multiple revisions would be used. This is not optimal and in ELISA's case especially, the mean value resulted in weaker model performance compared to others, indicating that there were more revisions that investors did not consider relevant. As noted earlier, there are differences between analyst forecast accuracies and how investors perceive them, which most likely caused poorer performance when revisions were mixed.

No lagged variables were used in making the forecast, which could be considered a shortcoming but since the purpose of the forecast was to solely examine how the revision data affects model performance, they were not necessary in this case. Accurate stock price prediction with the data available here is impossible, whether lagged variables were used or not. Inclusion of market or news sentiment, technical indicators and future earnings projections inter alia would be needed to increase the accuracy of a stock price prediction – and the model would have to be tuned accordingly. The results were insightful enough for the purpose at hand, and thus no further tweaks or data were needed.

Only three stocks were chosen for the analysis due to the time it took to run the model, which was three to four minutes per each forecast, two of which were made for each company. Due to this and the fact that the forecast was only used to review whether adding the target price variable would increase the model's performance it was decided that three stocks will do. Forecasts were also run for KONE but due to the similarity of the results FORTUM was chosen instead of it.

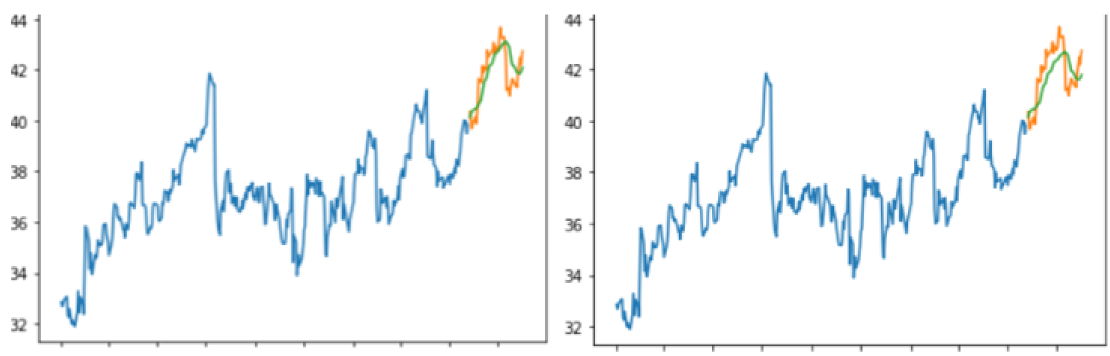
6.2 Model results

In order to objectively test the effects of target prices on forecast accuracy, a stock price forecast was for 47 days was made for three stocks; STERV, ELISA and FORTUM. These were picked due to good TPIR investment strategy returns in statistical analyses conducted earlier, which lead to the assumption that perhaps the target prices would be useful in terms of forecasting their stock price development. In the following charts the models' performances are showcased, with the benchmark forecast being on the left-hand-side and the revision-containing on the right-hand-side. The blue line is the train data, orange is the validation data and finally, green depicts the forecasted values.



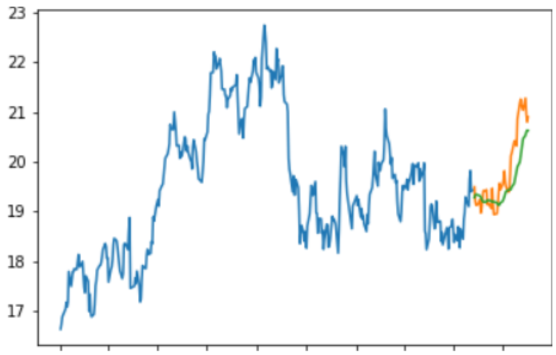
STERV 47-day forecast without target prices (MSE 0.229) STERV 47-day forecast with target prices (MSE 0.193)

Figure 12. STERV forecast results

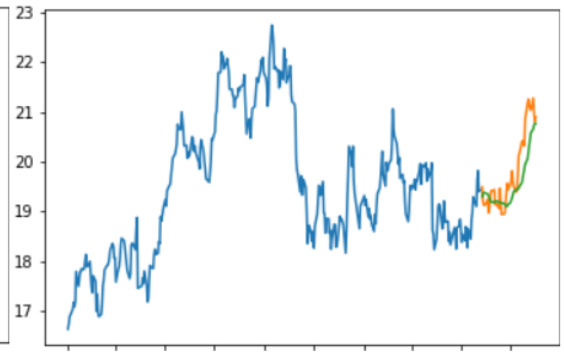


ELISA 47-day forecast without target prices (MSE 0.496) ELISA 47-day forecast with target prices (MSE 0.545)

Figure 13. ELISA forecast results



FORTUM 47-day forecast without target prices (MSE 0.226)



FORTUM 47-day forecast with target prices (MSE 0.202)

Figure 14. FORTUM forecast results

The accuracy was somewhat good in all cases, but this was mostly due to relatively steady price changes; once there was a major fluctuation, the model was unable to see that in advance which is understandable given the very basic variables used. Variable importance scores are tricky to apply to neural networks, and thus they were unfortunately left out from the analysis, and the author believes that MSE and the forecast figures are sufficient enough to judge whether target prices can help increase forecast accuracy. As mentioned earlier, the objective of the forecasts was not to tweak the model in order to get the best results, but rather to objectively test whether revisions help improve forecast accuracy.

The results were somewhat mixed, which might be due to several reasons. Both STERV and FORTUM saw lower MSE scores with target price values included, but this was not the case with ELISA. Given the stock's very stable long-term price development, the revisions reflected that and even the most optimistic target prices were not far off the then current price. It seems that despite the conservative revisions, the revisions drove positive returns which was also shown earlier in the TPIR investment strategy, but perhaps the model was not able to fully capture the often very positive receptions to conservative revisions, leading to higher MSE versus the benchmark. In other words, positive ELISA revisions seemed to indicate that the stock was close to its fair value, but these signals caused price hikes to reach or exceed target prices, which is relatively uncommon. Also, investor reactions seemed to depend heavily on the estimator and the use of mean revision values could have hindered the model's performance in ELISA's case especially.

Without mean revision values, the value-containing dataset was 40 rows longer than the benchmark in ELISA's case, i.e. 40 double-entries were present, and thus the training/validation cut-off day was different. One forecast was run with the double-entry dataset just for the sake of experiment, and its MSE was notably better than the other two.

This estimation is not comparable to the others, but it gives insight into the reasons that might have resulted in the differing model performance compared to STERV and FORTUM. As each estimator's revision value was included in this dataset instead of the mean value on multiple-revision days, the differing market reactions depending on the estimator could be better captured by the model, which could be a reason for the lower MSE score. The forecast horizon was different to the other forecasts, and hence it is unknown which factor had the highest importance in the increased model accuracy.

The results for STERV and FORTUM were more in line with the findings stumbled upon in the previous sections – that target prices affect stock prices somewhat consistently and carry relevant information for investors. Their forecasts, with target prices included, fared better than the benchmark, although the difference was narrowly smaller than in ELISA's case. The price variation of STERV and FORTUM was also smaller than ELISA's, which explain the lower MSE scores overall. The model's limitations were clearly observable in STERV's case where it was unable to capture the quick price changes during the forecast period, but it still achieved a low MSE as did FORTUM. The lack of data and additional variables clearly hindered the model's forecasting ability, which did not come as a surprise.

All in all, the results generally supported the view that revisions affect stock prices, but it was also obvious that the value itself is not the only relevant piece of information; the estimator issuing the target price is important likewise as mentioned earlier. The stocks were picked for the forecasting based on their performance in the TPIR returns evaluation and company-specific factors were considered as well. Estimations were made for KONE too, but the differences in results only came after the third decimal point and thus the results were not used due to being too similar.

The results weren't all in line, but the point of the forecasting was to objectively test whether target prices would be relevant for the forecast, i.e. do they consistently affect future stock prices in a way which would be beneficial in terms of forecasting. The results show that this is the case - revisions influence stock prices. This answers the first research question about the relevance of revisions for investors, while the earlier findings indicate that it is possible to exploit target prices to achieve high returns in short-term stock trading. The finding here that target prices have an effect on stock prices in general conflicts with the efficient market hypothesis, which answers the second research question about the efficiency of the Helsinki stock exchange from this theoretical standpoint.

6.3 Forecast result using estimators

Figure 15. ELISA LSTM forecast with Estimator ID (MSE 1.148)

Finally, Figure 15 above shows the forecast result for ELISA with the Estimator ID variable instead of target price value. This was tested since the results of combining revisions and estimators led to poor results, and it was found out that there are differences on the estimator level. The model performs worse than the one with values, which is logical. The MSE is notably greater than in the value versus benchmark case, indicating that the Estimator ID, a proxy for reputation, is not as relevant as the revision value, but given the findings in section five, it can be argued that it still carries relevant information in the eyes of investors. Unfortunately, the model was unable able to forecast the direction of the stock price even if it was able to identify differences between estimators since the values were left out in this case. As the model performance was so poor, it was only utilized in this case to provide some insight. Still, both variables carry relevant information that proved tricky to combine, as described next.

One-hot encoding the estimators was tested, but the results were poor with the MSE of ELISA being 4.7; significantly worse than in other predictions which had sub-one MSE scores when the value was used, and some 1.15 when the estimator ID was used. This may be due to the high number of NaN values, as most estimators had less than 20 revisions across the 397-day timeline. It was expected that this might result in worse model performance as there's not enough data for one-hot encoding to be useful, resulting in high numbers of NaN-values. Over 20 additional variables were also added due to the encoding, containing mostly empty data points, which also complicated the model, and furthermore some could perhaps be considered as unexplanatory variables. The number of variables added depended on the number of unique estimators for a stock, and if there were only a few revisions for a given estimator or if the accuracy was well off, those variables could be categorized as unexplanatory ones.

In terms of the model, NaNs were not a problem as LSTM is capable of handling them without issues, unlike some other algorithms. As the values were scaled between 0 and 1 before the forecast, filling NaNs was not an option and as mentioned, not necessary since LSTM was used. However, it was experimented during the analysis to see whether it would improve MSE, but the model performance suffered a lot – most likely after scaling.

All in all, despite the relatively simple data and model setup, the results were sufficient for comparison purposes and more light was shed on whether revisions do affect stock prices and if the value, estimator or both carry information that’s relevant to the market. The value-based forecasts were a compromise of sorts as encoding the categorical variables of Estimator IDs proved lackluster and the model did not perform as expected with them included, hence only the value was used in the forecasts. The Estimator ID does carry relevant information as well, but unfortunately combining the two did not produce the results here that were sought after.

7 Conclusions

Based on the statistical analysis and LSTM forecasting it seems that target price revisions do affect stock prices in the short-term. The sentiment seems to be more relevant than the scale of the target price, i.e. the signal to whether buy or sell is more important than the return potential in 12 months' time. Further, there are differences in how the market reacts to revisions by different estimators, while there are also variations between estimators themselves. Some estimators drive market reactions while others have very little impact, but these differences are not explained by target price accuracies or track record. It is not clear why the reactions differ, but some estimators provide a thorough analysis with the revision while others just give an updated target price, which might be one factor contributing to these differences. There are also differences between companies, although they are not as large as in the case of estimators. Thus, investors should familiarize themselves with how the stock price typically reacts to revisions by different estimators and seek for stocks that are more prone to short-term price reactions upon revisions. For instance, NESTE saw a high stock return during the 19-month timeframe but its revision-based trading returns were lower than that. This was mostly due to analysts being overly pessimistic about the company's earnings, but it goes to show that revision-based trading can also be less profitable than passive investing.

The research questions of this thesis were the following:

Do analyst target price revisions affect stock returns in the short term?

Could investors be able to benefit from an investment strategy based on these effects if they exist?

Would this investment strategy be viable in practice and what are the potential returns?

Based on the findings presented earlier, revisions seem to affect stock returns. The average stock turnover on revision days was 140 % higher than on regular days, while the mean three-day returns were 3.3 % around revisions compared to the full-year mean of 2.2 %. Given these results, it is quite evident that revisions cause observable effects on the market that drive stock returns. However, it was also found out that the revision signal seemed to have a bigger effect on returns than the implied return of the target price, i.e. investors don’t seem to care about the target price value as much as the signal to buy or sell.

To address the second and third research questions, based on the research and analysis conducted for this thesis it seems to be possible to achieve abnormal returns with a target price -based investment strategy in the Helsinki stock exchange. The aggregate return per stock using the 2 % rule in the investment decision making yielded an annualized return of 19.6 %, while the return from the 19-month data was 31.1 %. The average return from following TPIRs based on estimators was 10.0 % annually and 15.9 % from 19 months, while the OMXH25GI yielded 9.8 % from January 2018 to July 2019. For estimators with more than 30 revisions during the 19 months the mean return was 31.5 % - highlighting the differences between estimators. As a reminder, TPIRs equal or higher to -2 % were used as buy signals in the 2 % rule approach. There are, however, notable differences in returns between stocks and some fared much better than others. Given the relatively short timeframe of 19 months, it is not possible to say whether the returns would be consistent during a longer time period, but it seems that some stocks seem to benefit from target price revisions in terms of short-term returns consistently – and presumably will continue to do so in the future. For instance, ELISA saw minimal changes in revenue and profit during the time period but nevertheless, it achieved the highest returns using the revision-based investment strategy. KESKOB, a somewhat similar share in terms of revenue and profit growth, yielded negative returns by using the same approach; indicating that some stocks are better for the TPIR strategy than others. For high-growth and -return stocks like NESTE, the TPIR strategy is of little value as the target prices fail to keep up with the growing sales and profit figures.

An important aspect was also to examine whether the Helsinki stock exchange could be described as an efficient marketplace from the viewpoint of the efficient market theory, i.e. if new information is captured fully and quickly by the market. This was relevant as if target prices should affect stock prices, this hypothesis should not hold since target prices are based on information that is already been available for investors and thus should be reflected on the price of the security. As mentioned, target price revisions seem to drive stock returns at least in the short term, which was the scope of this thesis, and thus the Helsinki stock exchange does not meet the criteria of an efficient marketplace according to theory. While the efficient market hypothesis has been criticized for its shortcomings for a long time, and has also proved inconsistent due to, for instance, successes in technical analysis (Malkiel, 2003), it was selected as the theoretical framework for examining the implications of target price revisions for the author to have some theory to reflect the results on. The results, whether it be using revisions as signals for transactions or using target price data for forecasting stock prices, show that target prices affect stock prices and carry information that is relevant to investors, even though they are not based on information that is not already available for market participants.

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